MODELING NO-SHOW PASSENGERS ON PACOM EXERCISE AIRLIFT

GRADUATE RESEARCH PROJECT

Glenn S. Chadwick, Major, USAF

AFIT/MLM/ENS/04-02

DEPARTMENT OF THE AIR FORCE
AIR UNIVERSITY

AIR FORCE INSTITUTE OF TECHNOLOGY

Wright-Patterson Air Force Base, Ohio

The views expressed in this thesis are those of the author and do not reflect the official policy or position of the United States Air Force, Department of Defense, or the U.S. Government.

AFIT/MLM/ENS/04-02

MODELING NO-SHOW PASSENGERS ON PACOM EXERCISE AIRLIFT

GRADUATE RESEARCH PROJECT

Presented to the Faculty

Department of Logistics Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Masters of Logistics Management

Glenn S. Chadwick

Major, USAF

August 2004

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED

AFIT/MLM/ENS/04-02

MODELING NO-SHOW PASSENGERS ON PACOM EXERCISE AIRLIFT

Glenn S. Chadwick, MS

Major, USAF

Approved:

____________________________________ ________

Kirk A. Patterson, Maj, USAF (Chairman) Date
Assistant Professor of Logistics Management
Department of Operational Sciences

AFIT/MLM/ENS/04-02

Abstract

The issue of no-shows plagues many different industries that rely on reservation or appointment-type processes. Everything from the restaurant to healthcare to commercial airline industry has had to come up with solutions to this problem in order to remain both profitable and customer-service oriented. Many of these industries have used statistical models to predict no-shows such that seats or appointments that would otherwise go unused are filled with customers that were overbooked for those vacancies. This is a balancing act between trying to predict the number of no-shows and planning the number to overbook, without having more customers show up than able to accommodate, a dangling proposition. The military has been dealing with this same problem on its commercially chartered flights that move troops overseas for exercises, contingencies, and other requirements.

This research is aimed at using a statistical model to predict the number of no-shows on chartered passenger airlift for Pacific Command joint exercises to try to maximize the utilization of seats left unused by no-shows through overbooking techniques. If the number of no-shows can be predicted accurately, airlift planners will be able to overbook missions to fill those seats and minimize wasted resources. This will be done using a purely quantitative approach with correlation analysis and building a multiple regression model. The model will be built using both personnel and mission characteristic factors from historical airlift data from major joint exercises in the Pacific Command's area of responsibility.

Acknowledgments

A sincere thank you goes to Maj Kirk A. Patterson for serving as both a technical advisor and cohort in this research despite being deployed to Southwest Asia during the first portion of the effort. His guidance undoubtedly led to a much more detailed and thoughtful analysis of this problem.

Many thanks also go to several members of Pacific Command headquarters, Pacific Air Forces, and Headquarters, United States Air Force, for their immense help in providing the valuable data that was needed for this study. In particular, SSG Ketanoke Souza and TSgt Rosalyn Rosaldo from Pacific Command, SMSgt Eleanor Hills from Pacific Air Forces, and Lt Col Bruce Springs from Headquarters, United States Air Force, are given my heartfelt thanks for their tremendous help in making this a success.

Finally, I want to thank my fellow GLM IDE classmates for their camaraderie and friendship. This GRP and my success at AFIT would not have happened without them.

Glenn S. Chadwick

Table of Contents

List of Figures

List of Tables

Page

MODELING NO-SHOW PASSENGERS ON PACOM EXERCISE AIRLIFT

I. Introduction

Background

Each year, combatant unified commands hold a series of joint warfighter exercises that train not only their own troops for possible contingency, humanitarian, peacekeeping, peacemaking, and other types of missions, but also forces stationed within the continental United States (CONUS) by deploying them to the appropriate area of responsibility. United States Pacific Command, European Command, Southern Command, and Central Command all hold these exercises so that forces can obtain the training necessary to fulfill the command's mandated missions. Combatant commanders in the Department of Defense (DoD) perform these joint exercises within their area of responsibility under the Chairman, Joint Chiefs of Staff (CJCS) exercise program (CJCS 3511.01, 1999).

> *The CJCS Exercise Program, a key component of the Joint Training System, remains the principal vehicle for achieving joint and multinational/combined training. In addition to the obvious contributions to readiness and strategic access, this program provides significant political and diplomatic returns. Exercises demonstrate U.S. resolve and capability to project military power anywhere in the world in support of U.S. national interests and commitments to our allies. Additionally, the CJCS Exercise Program provides an opportunity to assess strategic transportation readiness and transportation supportability of operations across the crisis spectrum* (CJCSI 3511.01, 1999).

Combatant commanders do not have the requisite personnel and equipment under their command to perform many of these training scenarios on their own and must rely on CONUS-based forces to augment them. Thus, since most of these combatant commanders perform their exercises at overseas locations, one significant aspect of exercise success is to get the required personnel and equipment to the exercise locations. This is where the combatant commander relies heavily on the DoD's common-user strategic airlift and sealift forces (JP 4.01.1, 1996). This research will be restricted to the specific movement of personnel through airlift only.

Airlift plays a critical role in getting warfighters to the fight. The combatant commanders rely almost entirely on the United States Transportation Command (USTRANSCOM) to move these tasked forces from the CONUS to the location of the respective exercise, just as they would during wartime (JP 4.01.1, 1996). USTRANSCOM is comprised of a triad of strategic movement assets: airlift, sealift, and land movement resources. Specifically, USTRANSCOM's primary instrument for performing the airlift mission is through its component, Air Mobility Command (AMC) (JP 4.01.1, 1996). Air Mobility Command utilizes both organic military aircraft and contracted commercial airlift assets. These contracted commercial airlift assets are available through a program called the Civil Reserve Airlift Fleet (CRAF), an agreement between the DoD and many of the commercial carriers in the U.S. airline industry to provide wartime airlift needs in exchange for guaranteed peacetime business (JP 4.01.1, 1996). Thousands of personnel are transported annually utilizing these commercial airlift assets. The DoD's organic airlift fleet is generally comprised of cargo carrying aircraft such as the C-5 and C-17 aircraft, which either do not have the capacity to move the amount of troops required for exercises, or may not be available due to other worldwide requirements going on. Thus, for moving the bulk of the personnel required to perform a combatant command's exercise missions, just as they would a wartime mission, CRAF assets are used (Schmidt, 1997). In other words, most personnel will be transported to an exercise on a contracted commercial airline, from this point on referred to a charter, such as an MD-11 or DC-10 aircraft from the U.S. airline industry. To get to this point, extensive planning is conducted prior to movement.

The combatant commander will use a formal set of planning and execution tools such as DoD's Joint Operations Planning and Execution System (JOPES) and time-phased force deployment data (TPFDD) to arrange for this chartered airlift (CJCSM 3122.02A, 2000). Movement requirements are entered into a separate TPFDD for each respective exercise. Once all movement data such as unit name, unit type, number of personnel, location they require transportation from and to, and the timeframe that they need to be moved to get to the exercise to perform their mission, the TPFDD is validated by the combatant command to USTRANSCOM. USTRANSCOM will, in turn, pass the validated TPFDD to AMC who will schedule chartered airlift by contracting with commercial companies, such as World Airlines, for that airlift. Once the lift is scheduled, it will be put into movement execution systems that are accessible by deploying personnel to see when their movement is scheduled. To put this into an overall timeframe, the TPFDD planning process for an exercise starts roughly nine to twelve months before an exercise is programmed to take place and final movement schedules are generally available within three to four weeks before their execution. However, a considerable problem has been apparent in these charter airlift missions, and that is no-show passengers for the flights.

One of the objectives of this process is to efficiently use chartered passenger aircraft through maximum use of available seats. Despite the extensive planning that occurs, many planned seats on these missions go unused because personnel with reservations for those seats find other ways to travel to the exercise location, or they just fail to go at all. These "no-shows" are a detriment to the entire system in the form of wasted costs. Thus, from a combatant commander's perspective, which pays for these missions, it is imperative that personnel use the chartered airlift obtained by AMC for the combatant command.

Problem/Purpose Statement

Through this research, it will be shown that a large amount of all scheduled passengers fail to show for their chartered flights for exercises. As one would expect, this is a tremendous waste in not only a combatant commander's budget, as he or she is the one who pays for this airlift (CJCSI 3511.01, 1999), but also of American taxpayer dollars. Each seat that goes unused represents an opportunity cost and, if the passenger flies to the exercise location using other regularly scheduled airline flights, an additional burden is brought on the taxpayer's investment. This research will address this waste and try to determine some statistically significant factors that may relate to it. A quantitative analysis will be conducted to predict no-shows for individual missions which can then be used to maximize use of seats through overbooking techniques and, in turn, reduce overall costs for airlift in exercises. Through this analysis, an effort will be made to predict no-shows based on certain mission and personnel characteristics. From the researcher's experience and other literature (GAO, 1983), it appears that the no-show problem has been widespread throughout the military; however, this research will only look at a subsection of the entire DoD charter airlift needs for passenger movement—Pacific Command (PACOM) CJCS exercise requirements. From there, the model developed can be modified and used for other movement requirements for the entire DoD.

Research Question

What quantitative airlift and passenger characteristics are statistically significant in the prediction of no-show passengers on chartered passenger airlift missions for CJCS exercises within PACOM?

Research Objective

The purpose of this study is to devise a statistical model to predict personnel no-shows for PACOM exercise chartered passenger airlift missions in order to allow airlift planners to plan missions such that more seats are utilized through overbooking techniques. This could potentially save millions of dollars of DoD/taxpayer money by maximizing seat utilization and cutting the number of chartered missions overall. This money could then be used for other purposes such as increasing participation during exercises and achieving greater training opportunities.

Research Focus

The focus of this research will be on building a statistical prediction model for no-shows on chartered passenger airlift missions. From that, analysis could be conducted to determine how that prediction can be used to reduce costs associated with non-use of scheduled seats.

Investigative Questions

- What are the costs associated with no-shows?
- Historically, what have no-show rates been and are they a concern for commanders?
- How are chartered exercise passenger missions planned for and how may this contribute to no-shows for missions?
- How does the commercial airline industry model no-shows and can this be used to address the military's problem?
- Are there other industries with no-show problems with appropriate models that could be used to predict military airlift no-shows?
- Do passenger characteristics such as branch of service or reserve/active duty status have a relationship with higher or lower numbers of no-shows?
- Do passenger mission characteristics such as APOEs/APODs used, number of stops or flying time of missions, departure days or times, total number of scheduled passengers for a mission, or exercise location have a relationship with number of no-shows?

Methodology

These investigative questions and the overall research question will be answered using primarily quantitative analysis. The data used for this will come from logistics information systems such as the Global Transportation Network (GTN), managed by USTRANSCOM, and from the classified joint planning system JOPES. Although the data will come from this classified system, all data used for this research will be at an unclassified level. Actual ridership numbers from missions in PACOM exercises will be compared to the scheduled numbers to account for actual no-shows on the missions. Unclassified TPFDD data will then be used to determine what factors may be associated with the no-shows for each mission. In addition, commercial airline industry models for overbooking flights will be analyzed to determine if there are any similarities and possibility for use in this research. Multiple regression analysis will be used on the data to determine what factors may be statistically significant for predicting numbers of no-shows.

Assumptions/Limitations

No-shows may actually be caused by any number of factors, including commander influence, ignorance of the deployment system, poor deployment process training by particular units, and just plain neglect of the system. Commander influence may be from either trying to take care of his or her people by using unit funds for a more direct flight, or perhaps the mission timing does not meet his or her needs due to other meetings or requirements for his or her personnel within the unit. This research will not try to determine why there are no-shows for any particular mission, but only look at factors that may have a statistical relationship with no-shows. Additionally, due to time constraints of this research, extensive surveys of actual no-show passengers to collect data on possible personal factors such as the above will not be done. Since planning and execution procedures between the different combatant commands are relatively similar, this research using only exercises performed in PACOM's area of responsibility may be able to be used further for DoD use.

Chapter Summary and Preview of Remaining Chapters

This chapter provided the background for this research, defined the problem, outlined the research and investigative questions, and provided an overview of the scope and limitations of the research to be employed. This research will use quantitative data to examine factors associated with no-shows on chartered passenger airlift.

Chapter two will provide a review of associated literature on the topic broken up into three main areas. First, the process of planning and executing charter airlift missions will be discussed to lay a foundation for the use of some factors that may be statistically significant for predicting no-shows. Then, literature covering commercial industry problems with no-shows and the associated overbooking models of commercial airlines, civilian health care, and restaurant/hotel industries will be reviewed to find possible similarities with military airlift problems. Finally, the literature review will focus on published military academic material and DoD analyses for predicting movement characteristics to help formulate the model for this research. Chapter three will give a more detailed description of the methodology chosen for this research, why it was chosen, and how data will be gathered and analyzed.

Chapter four will provide the analysis of the data and lay out the results of the research and chapter five will provide the final conclusions in the form of an answer to each of the investigative questions and the research question. It will also address specific limitations of the research and recommendations for future research.

II. Literature Review

Introduction

A myriad of factors could lead to no-shows on flights and this research will be limited to those that are statistically significant and those obtainable from readily available resources. This literature review will be used to discuss these factors and their possible importance to this research.

To do this, it will be important to discuss the airlift system itself and how the so-called "gears" move in planning and moving personnel on chartered military airlift. The system will be described and defined using current DoD directives, manuals, and instructions. In some cases, the author will discuss possible problem areas with the current airlift planning and movement system and provide insights into possible improvements. It is important to note that the military airlift system is not designed specifically for efficiency, and the priority is to get people to the war or contingency area as quickly and effectively as possible, with a secondary emphasis on efficiency.

First, it will be described how joint exercises are planned in PACOM and from this, how airlift is acquired, or procured, from commercial airline companies to move exercise participants from both CONUS locations and some overseas locations, such as Hawaii and Japan, to onward destinations overseas where the individual exercises are held. In general, one can expect to have to move about 4,000 personnel a distance of over 6000 miles for most large exercises in the Pacific area. Second, as military airlift is not the only activity that sees the phenomenon of no-shows, this review will also look at other industries or businesses that have to deal with this problem and try to find any similarities and differences between those and the military. Intuitively, the commercial airline industry is the first place that will be looked at since one of its major objectives is also to move people from one place to another by air. Other industries reviewed will be restaurant, hotel, and healthcare where reservations and appointment processes are used, but result in some proportion of no-shows. Finally, the third section of this chapter will look at military research already accomplished on this phenomenon and compare and contrast it to this research effort. The author's previous military assignment was to plan and execute charter airlift in this manner and the problem of no-shows was discussed extensively and made a priority by combatant command commanders. Despite that, little was done to research the problem and seemed to be mostly dismissed as just a cost of doing business.

Military Charter Airlift Planning Process

Chairman of the Joint Chiefs of Staff Manual 3122.02A (2000), also known as Volume III of the Joint Operations Planning and Execution System (JOPES), defines the mobility planning system for all operational planning and execution of movement during contingencies, joint exercises, and other operations. This includes all movement via ship, vehicles, and aircraft utilizing either unit assets, organic common-user assets such as AMC's C-17s and C-5s, or commercial contract assets (JP 4.01.1, 1996). The latter two are used by all services to move their personnel and cargo and pay fees to USTRANSCOM, AMC's parent command, for their use (JP 4.01.1, 1996).

For exercise planning, the process can take several years before actual execution of an exercise; however, normal planning timelines are about nine months to facilitate a validated and executable time-phased force deployment data (TPFDD) document which is used by AMC to allocate airlift. During this nine-month timeframe, planners from all key areas such as operations, logistics, contracting, finance, engineering, intelligence, and communications from all the services and organizations planning to participate in an exercise will attend generally three planning conferences. They plan not only who and what (cargo) will be participating in an exercise, but also how they will get there and back. Airlift planners from the command sponsoring the exercise, in this case PACOM, as well as USTRANSCOM and Air Mobility Command, meet with members from each of the services to begin gathering the requirements for movement to determine the airlift requirements to move them. In addition to the conferences, planners collaborate through classified online planning systems to refine the requirements. PACOM is given an strategic airlift budget for their exercises which is then split into individual amounts for each exercise. The airlift planning effort is designed to take the exercise requirements and determine the cost of the airlift that will be required to move them, and then keep that within the given budgets of the exercises.

Since the exercise budget is used to move both personnel and cargo, the planners must determine how to move each. Most cargo gets moved by sealift as airlift is very expensive; however, since sealift is relatively slow, most passengers will move via airlift, or more specifically, chartered airlift (Schmidt, 1997).

Thus, planners continue refining requirements and enter them into the designated TPFDD that will be used to eventually assign airlift. The concept of the TPFDD is to try to consolidate movement requirements into movement timeframes, or windows, and from certain locations called aerial ports of embarkation (APOEs), the port that begins the strategic leg of movement, to aerial ports of debarkation (APODs). This consolidation is the airlift planner's primary goal as it creates efficiencies in movement and gains cost savings for the command funding the exercise. Movement windows are established to get people, and cargo, to the exercise location in time to be operationally ready to participate in the exercise. This may be a couple of days up to a couple of weeks before the exercise starts due to setup and training times. Movement windows are three-day movement increments (CJCSM 3122.02A, 2000) such that the planner plans to have an aircraft land in theater on one of those three days. Due to distances and flying times, the planner is also able to have an airplane land at the APOE to pick up personnel one day prior to the required arrival dates in theater (CJCSM 3122.02A, 2000). As a secondary note, these movement windows are smaller for reserve and guard personnel with a two-day window since their time allotted for active duty is limited due to civilian work requirements and each service's regulations. These movement timeframes may be critical when it comes to no-shows depending on the days of the week that flights are scheduled. In general, a large exercise can have about five different movement windows to consolidate as many passengers as possible, although a select few will not fit these due to other duty requirements. The setup of these windows drives the question of whether it is more likely that passengers may no-show for a flight that leaves on a weekend versus a flight that leaves during the middle of the week. This research will look at this characteristic as a potential statistically significant factor.

The different APOEs and APODs used for movements may also prove statistically significant to the number of no-shows for flights. Are passengers more likely to no-show if an APOE is at a military installation that may be more cumbersome to get to than flying directly into an international airport from where a military charter is departing? Also, in some instances, personnel may be required to actually fly in the opposite direction of their destination to meet a charter mission at an APOE that was planned as a central location to most of the personnel leaving at that time. For deployment of over 4,000 passengers for an exercise, possibly ten or more APOEs may be used as aggregation or dedicated pickup points and possibly two or three APODs for drop-off points depending on what areas the exercise takes place. Many personnel may not actually be assigned to work at the APOD and may then be required to travel on either additional theater airlift or ground transportation to a final destination. If an exercise participant utilizes regularly scheduled airline flights to get to the exercise instead of the airlift that was scheduled for them, they would be required to procure their own onward movement to their final destination. However, if they fly on the charter, they are either at their duty location already, since most charters will fly into military bases, or onward movement will be scheduled for them. This research will look at both of these factors, the type of APOE used and whether the APOD is the same as the final destination, to determine if they are statistically significant factors toward the number of no-shows. If proven to be significant factors, they could be managed by airlift planners in the planning process in the development of the TPFDD to help eliminate some no-shows from occurring in the first place. Exercises are actually comprised of two different movements, the deployment and the redeployment of personnel, both of which have their own distinct TPFDDs. For the purpose of this research, only deployments will be considered.

Again, the goal of the airlift planner is to aggregate passengers into planeload lot sizes, about 250 passengers for smaller requirements and up to 400 passengers for larger requirements (Air Mobility Command, 2003), by stopping at one or more, but usually not more than four, APOEs on a mission and going to one or two APODs. There may be several missions doing this within one movement window. Per planning guidance, planners normally will not plan to stop where there are less than 100 passengers (CJCSM 3122.02A, 2000), although exceptions are made. By planning missions to particular APOEs on a single flight, planners are many times constrained by times of the day, or even days of the week, they can route aircraft at each location due to quiet hours or operating hours at some airports or bases, thus having to plan some onloads late at night or early morning. For example, Yokota AB in Japan may limit times that aircraft can come into or go out of during daylight hours only, thus forcing missions going into there to have to onload at night at CONUS APOEs. This factor of onloading at night may prove statistically significant whether passengers are no-shows at these locations because of the timing of other connecting flights or just the inconvenience of trying to meet those times.

Although some units may code themselves in a TPFDD such that they can purchase regular airline tickets to get their people to an exercise at their own timing and expense, generally, the required method is by strategic airlift which is bought by the sponsoring command for the exercise. Most units are not funded for exercise travel costs; however, some may do so as a way to "take care of their people." Using strategic airlift, the unit will not have to expend funds for this movement except to move them to the nearest APOE to catch the charter mission. This is an important process because it allows the DoD to exercise a program called CRAF, or Civil Reserve Airlift Fleet.

CRAF is a program that allows the DoD to have exclusive access to civilian aircraft during times of war (JP 4.01.1, 1996). Presently, the government is contracted with commercial carriers to have almost one thousand airplanes at its disposal in the event of war (Dept. of the Air Force, 2004). By promising the DoD the use of these airplanes during times of war or other contingencies, the DoD also guarantees the civilian industry significant business during peacetime (JP 4.01.1, 1996). One part of this business is chartering their airplanes to move personnel during exercises. In addition, the government provides the commercial industry with the business of moving personnel around for their everyday jobs either for temporary duty (TDY) purposes or for movement of military families who are being transferred from one base to another. In all, this peacetime business can account for about $1.2 billion (Schmidt, 1997). In fact, the DoD relies on this program for about 40 percent of its movement capacity, both cargo and passengers, during wartime (Schmidt, 1997). During Desert Shield/Storm, Operation Enduring Freedom, and Operation Iraqi Freedom over 90 percent of the passenger movements were done using CRAF (Schmidt, 1997). Although it may be more convenient, and at times less expensive, to fly to an exercise on regularly scheduled airline traffic, the peacetime use aspect for the commercial industry is extremely important to the assuredness of having that capability in times of war, which is why it is critical to use this resource effectively for exercises. Appendix B, Table 11, shows how CRAF has been used in the past, reflecting its importance to the nation's defense. In addition, by using charter aircraft, units can be picked up at their own base and transported to another military base overseas where they will be working instead of having to fly into a civilian airport and then requiring extensive ground transportation to get to where they need to go. As discussed before, this may be a factor that affects the number of no-shows. Although some passengers could be moved on military aircraft (e.g. C-5), this is generally not done as these organic aircraft tend not to be very reliable as can be seen from their mission capability rates of around 65% for C-5s (HQ AMC, 2004a) and 80% for C-17s (HQ AMC, 2004b). When they break, passengers must be cared for and delayed in their movement, which can be costly to the exercise program.

The TPFDD is a database of separate line numbers, or more specifically unit line numbers or ULNs. A ULN is a person, a group of people, a piece of cargo (box, pallet, vehicle, etc.), collection of cargo, or a combination of people and cargo from a single unit that needs to move to an exercise together at a given time from the same place of origin to the same exercise location. A partial hypothetical section of TPFDD data is displayed in Figure 1.

ULN	Unit Name	U	S	Description	PAX	Origin Name	POE Name	M	S	POD Name	Dest Name	ALD	EAD	LAD	S
H0AP	UNIT A	A	M	ANALYST	1	MARINE BASE 1	HICKAM	A	K	U TAPHAO INTERN	BASE A	129	130	133	T
H0AQ	UNIT A	A	M	INTEL	1	MARINE BASE 1	HICKAM	A	K	U TAPHAO INTERN	BASE A	129	130	133	T
J3CRF	UNIT B	A	M	OPERATIONS	14	MARINE CAMP 1	KADENA AB	A	K	U TAPHAO INTERN	BASE A	124	125	128	T
J3CRG	UNIT B	A	M	LOGISTICS	1	MARINE CAMP 2	KADENA AB	A	K	U TAPHAO INTERN	BASE A	124	125	128	T
K25MP	UNIT C	A	A	MAIN BODY	126	ARMY POST 3	HICKAM	A	K	U TAPHAO INTERN	BASE B	124	125	128	T
K2BDA	UNIT D	A	A	ADVON	4	ARMY POST 3	HICKAM	A	K	U TAPHAO INTERN	BASE B	112	113	115	T
LF01	UNIT E	A	F	FUELS	1	AIR FORCE BASE 1	ANDERSEN AFB	A	D	U TAPHAO INTERN	BASE C	119	120	122	V
LF02	UNIT F	A	F	MAINTENANCE	1	AIR FORCE BASE 2	IWAKUNI MCAS	A	K	U TAPHAO INTERN	BASE C	124	125	128	T
M3AC1	UNIT G	A	M	STAFF	16	MARINE CAMP 3	KADENA AB	A	K	U TAPHAO INTERN	BASE B	129	130	133	T
M3AC2	UNIT G	A	M	STAFF	26	MARINE CAMP 3	KADENA AB	A	K	U TAPHAO INTERN	BASE A	124	125	128	T

Figure 1. Portion of Example TPFDD

As stated, ULNs can be made up of one person or many people and this could represent another statistically significant factor when it comes to no-show passengers. It may be easier for one unit to fly just one person to an exercise using its own funds; however, it may not be as easy for a ULN consisting of 20 people from one unit to do the same. Thus, this may show that individual ULNs have a higher positive correlation to overall no-shows than groups of passengers do.

Airlift requirements in a TPFDD is required to be validated to the AMC planner fifty days prior to the start of an exercise (CJCSM 3122.02A, 2000). Although this is the requirement, often some ULNs are not ready at that time due to sourcing or other problems. Thus, the ULNs that the airlift planner from Air Mobility Command has may not be all that will require airlift for the exercise, but is normally the vast majority. The planner may consider the possible future validation of ULNs and hold seats on planned missions for those passengers or may just overbook a plane based on a “best guess” of possible no-shows. Although this could be an important indicator of possible no-shows due to last minute assignments of ULNs to scheduled airlift, this factor will not be looked at in this research.

By filling up a charter aircraft, the planner tries to maximize all available seats. The number of seats scheduled to be filled on a plane may be an important factor in relation to the number of no-shows, as the more full a plane is, one may think the higher the possibility that there will be more no-shows.

Once the planner has formulated an airlift plan, the requirements will be given to commercial carriers, through DoD contracting officers, to fill the requirements. Once the contracts are let, they are passed back to the airlift planner who will then enter the missions and their associated ULNs into a computerized military movement system called the Global Decision Support System (GDSS), an Air Force command and control system for tracking, monitoring, and executing airlift missions. Most military units do not have access to this, thus other joint computer systems have connectivity to GDSS and pull necessary data for others to see. The two primary systems are JOPES and the Global Transportation Network, or GTN, an unclassified web-based system. One possible concern with JOPES has been that not all users have access to classified computer systems or access may be limited and not easily accessible. This may lead some units to not use them and become ignorant of the information they provide and then unknowingly schedule other flights for their personnel above and beyond the charter already scheduled for them, thus, creating a no-show. In addition, GTN is a relatively new system, still being refined, and has been hampered by its inaccuracy of data in the past **(**USCINCTRANS, 2000**).** Further research into this aspect may be worthwhile and could be accomplished through surveys of a sample of tasked units; however, this will not be accomplished here.

Once schedules are available, personnel are required to plan their movement to the APOE they are assigned to onload at. Many times, getting to the APOE can prove to be difficult as many of them may be at Air Force bases that are not close to a commercial airport and ground transportation to them may be limited and expensive. As discussed earlier, the type of APOE may be a factor that is statistically significant to the number of no-shows on a particular flight. Once at an APOE, the passenger is manifested on the charter flight and begins his or her journey to the APOD which may take them to as many as four or five en route stops along the way. Each en route stop has a couple-hour layover for either onload of additional passengers or possibly just for fuel. The two factors, number of stops and actual travel time, are possible statistically significant factors for this research.

Part of the basis for this research is to determine the confounding factors toward no-shows that are used in the planning and execution of exercise chartered airlift missions as discussed above and show how those factors may or may not correlate to no-show passengers on those missions. Thus, the airlift planning process and the characteristics of the missions themselves may or may not have a relationship to the number of no-shows on a particular mission. It is the goal of this research to find these correlations and attribute them to whether or not a particular person does or does not show up for his or her prescribed flight.

Related Commercial Industry Literature

The problem of no-shows is not a new phenomenon and certainly isn't limited to military charters. This problem exists in many different industries throughout the world. Many people who have flown on a commercial airline may have witnessed their flight being overbooked and having the gate attendant ask people on the flight whether they would volunteer to remove themselves from the flight in exchange for either a later flight or some kind of cash incentive plus a later flight. Overbooking occurs because airlines are trying to maximize use of seats based on a historical no-show rate of passengers with confirmed reservations. Overbooking has occurred since the end of World War II when supposedly important passengers (military, political figures, etc.) were, by law, given priority to board flights (Ruppenthal & Toh, 1983) in place of a "normal" passenger. This was soon put to an end, but overbooking continued until antiquated reservation systems were replaced with improved processing systems and began to keep the overbooking problem to a minimum for awhile. However, in 1976, consumer advocate Ralph Nader was a victim of airline overbooking and sued Allegheny Airlines for its failure to provide him a seat on a flight for which he had purchased a ticket and had a confirmed reservation" (Ruppenthal & Toh., 1983). The court decided that this was grounds for awarding damages and now airlines are required to give cash or other flight incentives for a passenger that either voluntarily or involuntarily gives up a reserved seat. Although currently only about 0.8 in every 10,000 passengers is denied boarding due to overbooking by the airlines (Peterkofsky, 2002), it is much more expensive for them to deny a seat to someone than it is to allow a seat to go empty (Ignaccolo & Inturri, 2000). Thus airlines have been looking for ways to minimize overbooking and compensation costs, but at the same time maximize utilized seats. In these cases, the airlines have used overbooking models designed to take into account average demand, cancellation, and no-show data for a particular flight over its recent history to calculate how many seats to sell prior to departure. There are many different models for performing this that will be discussed and compared to the topic of this research. In addition, the no-show problem exists in other industries as well such as restaurants, hotels, and healthcare, to name a few. These will be discussed later in order to develop ideas for determining whether certain factors used by them may be applied to the military charter no-show problem.

First, there has been considerable research and literature devoted to the commercial airline industry in terms of overbooking and demand forecasting models. Smith, Leimkuhler, and Darrow (1991) of American Airlines Decision Technologies estimated that nearly 50% of all reservations in the airline industry resulted in cancellations or no-shows. In addition, they (Smith et al., 1991) estimated that roughly 15% of seats on all airlines will be empty on flights that were sold out prior to departure. At times, it was estimated that the no-show rate was as high as 20% (James, 1982). Ruppenthal & Toh (1983) suggest that no-shows may result from three general types of causal factors: intentional, unavoidable, and inadvertent. With these high cancellation and no-show rates, the airlines have been forced to overbook many of their popular flights in order to assure they fill as many seats as possible to realize a profit. With deregulation occurring for the airline industry in 1979 and competition in terms of price becoming the way airlines differentiate amongst themselves, companies must ensure that they get all the revenue from sales of tickets that they can and cut costs as much as possible. Unfortunately, cutting costs reaches a limit and much more becomes increasingly difficult, which leaves airlines with trying to produce as much revenue as possible. One of the ways to do this is through overbooking flights in the hopes of filling seats that become vacant due to no-shows. However, there must be a balance between the cost of letting a seat go empty and the cost of having more passengers than seats.

Research for this problem has been seen as far back as an optimization model produced by Beckmann (1958), before the advent of the jet airline age. This was followed by other research by Thompson (1961), Taylor (1962) of British European Airways, and Rothstein and Stone (1967). These early models' main focus was determining booking limits for reservations within a single leg of a flight and mostly within a single fare class and disregarded any level of managing revenues. However, they did account for cancellations and no-shows as well as customer-service levels. By the early 1970s, that research developed into models that were designed to optimize revenue such that the most revenue could be realized with the uncertainty factors of demand, cancellations, no-shows, and standby passengers. These models looked at the nature of two or more fare classes of tickets as well as two or more booking periods (Littlewood, 1972). Fare classes are distinguished usually by how far ahead of time one books a seat as well as tickets that may have different restrictions with them such as Saturday night stays or partially non-refundable tickets. Booking periods are set timeframes before departure when tickets may be sold at different prices. Other models such as Curry's (1992) have suggested refinements to the earlier models by integrating dynamic approaches to the overbooking problem such as allowing higher fare classes to book from lower fare seat inventories. In 1987, Belobaba (1987) generalized Littlewood's rule (1972) using multiple periods for obtaining seat allocations to two fare classes. This model is called the Expected Marginal Revenue Method (EMSR). Most of these models now fall under Perishable Asset Revenue Management (PARM) theory developed by Weatherford and Bodily (1992), essentially entailing how airlines segment their fares and cabin classes and structure different time frames for advance ticket sales. This is unlike how military charter flights are booked which is basically all at one time. Thus, these commercial airline models cannot be used as they are for this research. A visual depiction of what overbooking models attempt to do is shown in Figure 2.

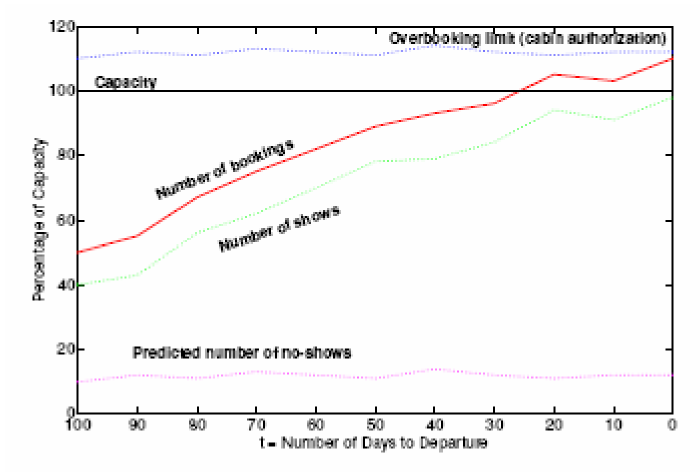


Figure 2. Overbooking Graph (Lawrence, Hong & Cherrier, 2003)

From these models earlier models, airline yield management has continued to grow by trying to incorporate the best ways to allocate seats to different fare classes at different booking periods in order to maximize revenue, and thus profit. Many airlines' computerized reservation systems have adopted these models that will automatically determine what seats are left in which fare classes on a continuous basis so as to maximize the allocation of the highest fare seats given probabilistic demand, cancellations, and no-shows. This tries to fill as many seats as possible without having more people show up for a flight than there are seats available on the plane (Davis, 1994). Another aspect to this is that many airlines sell tickets that are non-refundable with several other restrictions; however, these tickets are also discounted much more than others. When a non-refundable ticket is not used and the airline overbooks and fills that seat with another revenue creating passenger, it is double selling that seat. This double selling may run as high as three-fourths of the seats on some flights (Farnham, 2001), however, this may be the exception and not the norm. It could be argued that passengers with low fare tickets are less likely to be a no-show as they would be out the entire amount of the ticket. Regardless, the airlines must account for these no-shows as well which just helps their bottom line even more.

Recent work continues to improve revenue management for airlines using dynamic models for airline seat allocation. Zhao and Zheng (2001) performed research with passenger diversions and no-shows being static across different classes such that some passengers are flexible and will pay a higher fare if a discount fare is not available. Other work (Freisleben & Gleichmann, 1993) use different approaches such as neural networks that learn to approximate the mapping between the input data (the number of booked seats for each reservation class at distinct time periods prior to departure) and the desired output (the number of no-shows) in order to make future predictions.

Overall these overbooking models have been estimated to save the airlines about 50% more than their net profits (Davis, 1994). Robert Crandall, former Chairman and CEO of AMR (American Airline's holding company) and president of American Airlines states, "Revenue management is the single most important technical development in transportation management since we entered the era of airline deregulation in 1979" (Zaki, 2000). The art of revenue management has become more than just counting seats on an aircraft, it “requires something close to rocket science to sell seats and make money (Davis, 1994).” American Airlines has saved $1.4 billion in the period from 1982 to 1992” (Davis, 1994).

Although these commercial airline models can perform well in revenue management scenarios, several of the major factors, booking timeframes and fare allocations, used in them don’t correspond to how military charter flights are managed. However, similarities exist in using historical data for particular flights to predict future no-shows such as times of flights, days of the week for flights, and routing of flights. So flight characteristics like these will be pursued in this research to build a predictive model for military charter no-shows.

In addition to the commercial airline industry, other industries also experience problems with no-shows that not only tighten their profit margins, but also disrupt their reservation and appointment processes. Three of the major industries facing this problem are restaurants, hotels, and healthcare, although theatres, auto rental agencies, barbers, and others experience this to a degree as well (Ruppenthal & Toh, 1983). Research in these industries is a little different as they don’t specifically plan for no-shows and then overbook. Instead, they offer incentives or have reminder systems for customers to keep reservations or monetary penalties may be levied for not showing. These industries put more emphasis in trying to fix the no-show problem instead of covering its symptoms. This is particularly true in the healthcare industry. Healthcare businesses use telephone or postcard follow-ups to remind patrons of their appointments (Garuda, Javalgi, & Talluri, 1998). This idea would seem to have its merits for exercise charter airlift, but usually each component (Air Force, Navy, etc.) only has one or two people managing hundreds of ULNs for the combatant commander and this task would take an enormous amount of time that is not available during a short deployment timeframe (only about 4-5 weeks). Hotels and restaurants use monetary penalties to influence patrons to keep reservations by applying a no-show fee to credit cards given upfront as a guarantee. Restaurant businesses can typically have over 25% no-shows on any given day (Miller, 1992), and unless they can make that up with walk-in customers, they stand to lose considerable revenue. Miller (1992) goes on to state that this trend may reflect an era where social niceties hold less importance and personal obligations to honor agreements have eroded. Restaurants do not typically gather personal data on their customers in order to determine what kind of people are no-shows more than others, however, they do still use timing factors such as times of the day or day of the week to determine when no-shows are more likely to occur (Miller, 1992). Again, this factor could be useful in a model for predicting no-shows on military charter airlift. This is true with the hotel business as well. Ruppenthal & Toh (1983) report that in a small sample taken in Seattle, some 5-10% of the persons making non-guaranteed reservations fail to show up. Hotels use many of the same factors for determining no-show rates as restaurants and airlines use, such as days of the week, time of year, and booking lead times (Ruppenthal & Toh, 1983).

The healthcare profession is also concerned with the number of no-shows since each patient that fails to show for an appointment is lost revenue opportunity. Broken appointment rates generally range from 15-30% (Bean & Talaga, 1995). Some healthcare businesses also charge penalties for not showing up for an appointment, but others determine that penalties create long-term negative implications with not keeping that patient, thus further reducing overall potential revenue (Garuda et al., 1998). One area that healthcare businesses do try to correlate with no-shows is a patient's characteristics such as age, gender, socio-economic status, and previous no-show history (Garuda et al., 1998). Additionally, Garuda et al. (1998) discuss situational characteristics such as day/time of appointments, lead times for appointments, and transportation aspects of getting to an appointment. Bean & Talaga (1995) studied other research and discovered that demographic characteristics have been inconsistent with determining numbers of no-shows, but did feel that interactions between situational factors and patient characteristics as well as the main effects themselves could affect no-shows. This is an important finding and may prove useful for this research by interacting passenger characteristics with mission characteristics. However, instead of trying to determine how to counteract no-shows through some kind of overbooking model, the healthcare industry is more determined to eliminate the no-show problem as much as possible by first finding out who is a no-show and why, and then implementing programs to encourage patients to show up for their appointments (Garuda et al., 1998). Garuda et al. (1998) perform research using this approach by supporting programs such as telephone and postcard reminders, contracting with patients, educating patients on the effects of no-shows, offering incentives, reducing the effort for a patient to show, and charging service fees for not showing. Eliminating no-shows altogether would be the preferred choice for military charters, however, there are no real incentives that can be offered, and imposing monetary penalties would be much too burdensome (GAO, 1983). However, the fact that the healthcare industry does look at personal characteristics to determine predicted no-shows, a similar approach will be used for this research. For example, the service that a member is from or whether they are from the Guard or active duty force may be able to be used as a predictor of no-shows for charter flights.

Military charters are managed a little bit differently than the commercial industry. Military charters do not run on a revenue or profit-based objective. They instead are cost-based and linked to other more intangible factors such as amount of training received or combat readiness potential received, as in the case for exercises. This is difficult to measure, but is invariably the most critical aspect in the national defense of the United States. Thus, the revenue management models discussed may not be appropriate to the problem at hand, but they do have some similarities that will be furthered upon in this research. All of the commercial models are generally built using demand and no-show data from similar types of flights or reservations, during similar times of day or days of the week, and similar routes. Some factors affecting passenger demand include flight time, nonstop versus connecting flights, time required for the complete trip, price, restrictions and penalties, etc.(Davis, 1994) which can also be used to show possible patterns in military charter no-show passengers. As in the commercial models, this research will use historical data to create the model, although unfortunately, data is not nearly as extensive as can be obtained from, say, the commercial airlines. The commercial airlines can have the same flight running several times a day, every day of the week, throughout the year. Thus, the data available for measuring no-show statistics for them is tremendous. Davis (1994) compares this to other industries and finds that the airline industry has the best data in terms of volume, length of history, and quality. Military charters for an exercise may run twice a week for about a month and have varying pickup and drop-off locations.

Only a few selections of literature were found that researched passenger-specific features, one being Lawrence, Hong, and Cherrier (2003). They (Lawrence et al., 2003) retrieved data from Passenger Name Records (PNRs) from Air Canada's reservations system which included frequent flyer status, where the ticket was booked, gender, number of passengers booked on the same series ticket (family or group travel purchase), and meal type, as well as several flight-specific factors. Again, the data for their research was extensive compared to what is obtainable on military flights in that they included 1.26 million PNRs on 15,019 flights in a three-month period to formulate a regression model for no-shows (Lawrence et al., 2003). They were able to conclude that their model "incorporating specific information on individual passengers could produce more accurate predictions of no-shows than conventional, historical-based, statistical methods" (Lawrence et al., 2003). As all the models discussed here are based generally on historical data, it must be acknowledged that these are useful for predictions and forecasting, but forecasts in themselves are never perfect.

A clear difference between the commercial industry and the military is in each one's objectives or goals. The military has a mission to get done which is often intangible and it will get done, in most cases, regardless of cost. The commercial industry's objective is to maximize profit to stay in business, and although sometimes it will forego cost to serve a customer better, that additional cost may actually bring increased goodwill to the business for future profits.

Related Military Literature

Some literature on the topic of military movement no-shows was found, but was limited. Although extensive studies on the capabilities of CRAF and the incentives for the program are available (Schmidt, 1997; Curtin, 2002; Graham, 2002), little has been done to discuss the no-show problem on this type of airlift.

A GAO Report Analysis (1983) discussed the no-show problem and essentially confirmed that this phenomenon has existed to some extent for many years now. This report found a no-show rate of 14.7% (GAO, 1983) in the early 1980s which will be used as a comparison to current no-show rates to be determined by this research. If they are similar or if current charter no-show rates are even higher today, this will add to the validity of a model built in this research to be able to predict no-shows consistently over time. The report (GAO, 1983) found that the no-show rate for contract airlift flights had actually increased from the period 1976 to 1983 by over 4% based on additional military service reports done during this time frame. The report also states that the no-show rates were aggregate for all the services and did not try to analyze trends applicable to each military service (GAO, 1983). This factor seems significant as each service has different cultures and different attitudes about airlift for its personnel and the funds required for that airlift. The 14.7% no-show rate was estimated to cost the government over $13 million annually (GAO, 1983) which was most likely conservative as it did not discuss whether these no-show passengers actually acquired other transportation using government funds instead of the provided air transportation. The same rationale can be used for exercise charter airlift.

The cost for a seat on a charter mission varies according to the actual number of miles flown and the number of seats bought for the mission (Air Mobility Command, 2003). Each year new rates, published annually by Air Mobility Command, are paid to commercial carriers for chartering their aircraft to the government to move military and other government personnel. The rates will vary by type of aircraft used, narrow body or wide-body, and by the type of trip the government requires, round-trip or one-way. For exercises, missions are generally one-way since there is only a need for deployment at the beginning of the exercise. On occasion when certain exercises overlap each other, missions are able to be bought round-trip to move troops to their exercise and then fly to another location to pick up passengers that need airlift home from their exercise. Thus, several variables determine the cost of a single mission. A mission from Hawaii to Korea, for example, would normally have a charter aircraft having to position from somewhere in the CONUS to Hawaii and then contract for a certain number of seats from Hawaii to Korea. To move 360 passengers, for example, an MD-11 wide-body aircraft may be used (Air Mobility Command, 2003). Statute seat-miles is the measure used for determining the variable cost of a mission. The current contract rate per statute seat-mile is 15c/mile for a one-way charter, and about half that for a round-trip mission (Air Mobility Command, 2003). Also, if the aircraft must position to Hawaii for the flight, another rate is added which is about half the rate for the active part of the mission, which is the Hawaii to Korea segment. Thus, to contract an aircraft to move 360 passengers, it will cost about $325,000. This assumes that the aircraft does not have to deposition back to the CONUS empty after the mission is done which could add an additional $100,000. This is generally a valid assumption since planners will usually try to utilize the back end of a mission for something else such as a unit move. In addition, mission costs may vary from the rates given as carriers who bid for these flights may try to run missions more efficiently by planning them one after another with the same plane if possible, thus cutting down on positioning and depositioning costs. Therefore, the statute seat-mile rates are only a guide, but based on the researcher's experience in this field, generally give close estimates to final costs. Therefore, a flight from Atlanta to Korea may cost roughly $500,000 while a mission from the West Coast of the United States to Korea may cost about $400,000. Being conservative and using this last cost figure of $400,000 to allocate 360 seats for passenger movement, the average cost per seat of any charter mission is around $1,100. Thus, for every no-show, the government could lose around $1,100. Over the course of an entire deployment utilizing ten charter aircraft, a fifteen percent no-show rate could cost over $500,000 in non-utilized reserved seats, the cost of an entire charter.

The GAO study (1983) also found that many no-shows are a result of invalid reasons such as poor travel planning or simply not showing up for the flight due to making other travel plans and not canceling their contract airlift reservation. This, again, could be a result of passenger specific characteristics such as branch of service or status of member (active duty or reserve). The GAO report (1983) stipulates that many times units will buy commercial tickets for their personnel because they are cheaper than the tariff for the contract airlift, despite already having a reservation on the flight. Then they fail to cancel that reservation. The problem for this research is different as the charter flights used for exercises are bought by the unified command holding the exercise and not through funds paid by individual units. Thus, the exercise flights should theoretically draw more passengers and less no-shows since there is no monetary cost to the unit. Another important distinction between the types of flights in the GAO report (1983) and those in this research is that the flights in the report are channel missions and run on a scheduled basis, e.g. once or twice a week, whereas exercise charters are not on a recurring time schedule. Finally, with channel flights, passengers are typically individuals, or possibly with family members, who are not part of a group in their travel. These personnel may be permanently changing stations to an overseas area or coming back to the CONUS from an overseas area. The factor of having single-person requirements scheduled on airlift may play an important part in the number of no-shows for a flight, and will be included as a possibly important variable in this research as well. The no-show problem on contract airlift appears to be endemic, and although some incentives, and penalties, have been used to try to curb this, not much progression has been made (GAO, 1983).

Additional research has been conducted by graduate students in this area, but has been limited to cargo movement problems associated with poor TPFDD planning and poor marking of pallets of cargo as in Browne's research (2000). Correlation and regression analysis was used by Browne (2000) using military movement characteristics such as locations and type of aircraft as factors for reporting relationships to predicted moves. In the conclusion of the research, the author (Browne, 2000) discussed why analysis of passenger movement was not done. AMC "assumed" that the delivery of soldiers to the theater would take place one way or another (Browne, 2000), but the research does not discuss how they get there nor show any historical patterns for no-shows due possibly to passengers finding other ways to travel.

Another graduate research paper discusses the problem of a portion of contract charters called Category B missions which are primarily used to move members and their families being reassigned (permanent change of stations, or PCS) to or from overseas locations (Pike, 1998). This paper (Pike, 1998) discusses the difficulty of making this system run efficiently due to limited movement times and onload/offload locations, especially for members returning from overseas locations. The research did not discuss actual quantitative no-shows, but did reveal some of the reasons for this occurrence. Category B travel is similar to exercise movements in that personnel are booked on the flight usually weeks in advance of departure, however, PCS personnel are more likely to want to deviate from Category B movement schedules than exercise passengers in order to take leave en-route to see family or friends after a long assignment away from home. This often means that going to a particular APOD on a Category B mission is not the most convenient or cost effective for the member and thus they, and their commanders, procure another way to move via normal commercial airline ticketing, thus presenting a no-show for the Category B flight if the reservation is not cancelled. Although limited in availability, the literature on military concerns for no-shows does give this research a stepping stone to use in regards to the factors discussed.

A final note should be made about no-shows and the overbooking philosophy of commercial airlines. Even though elaborate models may be developed to predict levels of demand and no-shows for particular flights, many managers, both military and civilian will still utilize their gut feel or intuition to make decisions about appropriate problem areas despite what the models say. One model developed by Ignaccolo & Inturri (2000) uses a Inference Fuzzy system as a decision support tool to assist in revenue management actions. The airlines often allow the intervention of a booking analyst to override the automated system's overbooking advice in order to embody common feeling and human judgment in unusual situations (Ignaccolo & Inturri, 2000). Military airlift planners also must use their judgment in overbooking charter airlift missions, but currently that is all that is used as no mathematical or statistical model is available to assist in this matter.

Although the literature review did not find any precise predictive models that can be used directly with this research, it did uncover how many of the statistical and analytical models correlated either product/service or personal characteristics with no-shows. Many of these factors, and others similar to them, will be used for this research as a starting point towards building a predictive model for military charter no-shows for PACOM missions.

The next chapter will describe the methodology to be used to gather and arrange data and the variables or factors to be used for the predictive model.

III. Methodology

Introduction

Chapter three will explain the methodology used for this research to meet the objective of creating a model to predict the number of no-show passengers on a military charter airlift mission for a PACOM CJCS exercise. As discussed in Chapter 2, numerous factors will be looked at to determine possible relationships with numbers of no-shows. These factors can have either a negative or positive relationship with the number of no-shows. Although not all possible factors that may have a relationship with no-shows will be analyzed for this research, the ones that are will provide a starting point for analyzing this phenomenon where little other research has been accomplished. After reviewing the literature available, it was determined that correlation and regression analysis would be effective tools for this research since data from several different factors can be related to no-show data in this manner. The second section of the chapter will be used to define the purpose of this research. The third section will describe the research paradigm, quantitative or qualitative analysis, to be used. Section four will describe and define the data to be used, the format of the data, and the sources for obtaining the data. The next section will briefly delineate some of the limitations and assumptions of the data to be collected. The sixth section, and probably the most important, will be the basis of the research by describing the model-building methodology to be used for obtaining the theoretical model for predicting no-shows using a wide variety of different factors.

Purpose Statement

The purpose of this research is to build a statistical model for use in predicting the number of no-shows on exercise charter flights which can then be used to maximize the use of seats on these missions through overbooking techniques. The intent is to minimize wasted resources and save funds that can be used for more value-added endeavors by commanders such as additional training opportunities.

Research Paradigm

This research will be a quantitative analysis using historical data to find correlational and linear (or possible non-linear) relationships between several independent airlift mission and personal passenger factors with the proposed dependent variable, the number of no-shows on a mission.

Data Sources/Format and Variables

Since this study will use correlation and regression analysis, an extensive amount of data needs to be collected in order to make as accurate a prediction as possible for no-shows on charter airlift missions. This will be done by gathering a number of different types of data on individual charter missions from different exercises. For each mission, personal and airlift mission characteristic data will be collected in a format that can be used for analysis. As discussed in the literature review, several movement characteristics for individual missions will be used as well as several personal characteristics of the passengers themselves on each mission.

JOPES databases are the official records for all contingency and exercise movement plans for PACOM and other joint commands. JOPES contains all the planned movement data for joint exercises in the form of TPFDDs. In addition, each service's major commands use JOPES to document all their service-specific exercise movements, although those will not be analyzed for this research effort. TPFDDs contain both specific passenger data and their associated movement requirements. Thus, it was apparent that this database should be the one used to collect the planned movement data for this research.

TPFDD data is accessible in a couple of different ways. One is through a classified system called the Global Command and Control System (GCCS) which is accessed through its own network of dedicated computer databases. JOPES is a subsystem of GCCS. GCCS will not be readily available to the researcher; however, another method of access called Web-Hoc Query, accessible through any classified, or Secure Internet Protocol Network (SIPRNET), computer's internet connection, will be. This will be used to pull data from the JOPES databases. The query program is user-customizable in web-based format and allows the extraction of specific data required from either historical or current TPFDDs. Queries will be performed for all exercise deployments over the last three years using this method. Although data further back than this could be obtained from archived databases on backup media, it would require extensive coordination and approvals, taking considerable time that is not available to the researcher for this study.

To make the TPFDD data usable for quantitative analysis, it will be copied from the Web-Hoc Query webpage output and converted into spreadsheet format for easy manipulation to extract totals of certain types of passengers (active duty, service, etc.)

scheduled on flights as well as locations they were scheduled to move from and to and timeframes they were scheduled to move. This spreadsheet manipulation will be done using Microsoft® Excel, using all the TPFDD information obtained for each exercise. Each exercise TPFDD is sorted by ULN. Each ULN will be aligned in rows and contain that ULN's movement data. The specific TPFDD data queried will be the ULN, service code (Marine, Navy, etc.), component code (active duty, guard, or reserve), number of personnel on the ULN, origin of ULN movement (home base or city), APOE of ULN (where ULN was assigned to load on charter airlift), mode/source for ULN (code showing if ULN was moving by strategic airlift, sealift, ground, etc.), APOD (where ULN was assigned to offload from charter airlift), destination (where ULN was tasked to deploy and work at), movement time parameters or window, and validation code (shows if ULN was validated for movement). Again, a portion of a sample TPFDD was shown in Figure 1 of Chapter 2. For the purpose of this research, only ULNs that had a mode/source code of A/K will be used since that code represents strategic airlift, which is how charter airlift is categorized.

To link each ULN with a specific charter mission, again JOPES was used. The JOPES database interfaces with several in-transit visibility and movement systems to include GTN and GDSS. Although data is not stored in these latter two systems for more than a couple of months after mission execution, the movement data from those systems automatically flows to JOPES and remains available in the JOPES database for several years until they are archived by PACOM personnel after about three years or so as described earlier. The airlift schedules that show each ULN and the mission it's scheduled on can be pulled using something called a Scheduling and Movements query, also done through the Web-Hoc Query page. With this data, each exercise spreadsheet will show both the ULNs with their movement requirement and the missions the ULNs were scheduled on as shown in Figure 3.

Mission #	ULN	Unit Name	U	S	Description	PAX	Origin Name	POE Name	M	S	POD Name	Dest Name	ALD	EAD	LAD	S
J414CG	H0AP	UNIT A	A	M	ANALYST	1	MARINE BASE 1	HICKAM	A	K	U TAPHAO INTERN	BASE A	129	130	133	T
J414CG	H0AQ	UNIT A	A	M	INTEL	1	MARINE BASE 1	HICKAM	A	K	U TAPHAO INTERN	BASE A	129	130	133	T
J409CG	J3CRF	UNIT B	A	M	OPERATIONS	14	MARINE CAMP 1	KADENA AB	A	K	U TAPHAO INTERN	BASE A	124	125	128	T
J409CG	J3CRG	UNIT B	A	M	LOGISTICS	1	MARINE CAMP 2	KADENA AB	A	K	U TAPHAO INTERN	BASE A	124	125	128	T
J405CG	K25MP	UNIT C	A	A	MAIN BODY	126	ARMY POST 3	HICKAM	A	K	U TAPHAO INTERN	BASE B	124	125	128	T
J401CG	K2BDA	UNIT D	A	A	ADVON	4	ARMY POST 3	HICKAM	A	K	U TAPHAO INTERN	BASE B	112	113	115	T
J909CG	LF01	UNIT E	A	F	FUELS	1	AIR FORCE BASE 1	ANDERSEN AFB	A	D	U TAPHAO INTERN	BASE C	119	120	122	V
J407CG	LF02	UNIT F	A	F	MAINTENANCE	1	AIR FORCE BASE 2	IWAKUNI MCAS	A	K	U TAPHAO INTERN	BASE C	124	125	128	T
J411CG	M3AC1	UNIT G	A	M	STAFF	16	MARINE CAMP 3	KADENA AB	A	K	U TAPHAO INTERN	BASE B	129	130	133	T
J409CG	M3AC2	UNIT G	A	M	STAFF	26	MARINE CAMP 3	KADENA AB	A	K	U TAPHAO INTERN	BASE A	124	125	128	T

Figure 3. Example TPFDD with Mission Data

Since not all of the missions shown will be charter passenger missions (some may be cargo missions), the data will be reduced to just those ULNs that are scheduled on charter passenger missions. This will allow for statistics on the variables to be tabulated on each mission for use in the analysis.

Another important resource that will be used for data collection is the Pacific Airlift Management Office assigned to Pacific Air Forces in Hawaii. This office manages and executes exercise airlift on behalf of PACOM. It will provide Microsoft® Excel spreadsheets that show essentially the same TPFDD data as discussed above with each ULN in the exercise TPFDD and the mission it was assigned to move on. These spreadsheets will also contain all the actual mission schedules for the charter airlift that will be used to compile mission characteristic data for each flight, such as time of day, day of week, number of stops, and travel time. This information combined with the TPFDDs and movement data from earlier will provide all the information needed for the independent variables for this research.

The variables to be used for this research and a short description of each are found in Table 10 of Appendix A. To determine the values for each variable for each mission in the data set, pivot tables within Microsoft® Excel will be produced showing total numbers of different types of scheduled personnel (active duty, guard/reserve, Army, Air Force, etc.) and total numbers of scheduled personnel loading at different types of APOEs for each flight. Three different types of APOEs will be used for this research as shown in Table 10, Appendix A. Grouping of individual APOES into one of these three categories will be done manually based on the criteria shown in the variable definitions. The variable showing the percentage of passengers that had to travel in a reverse direction from their final destination in order to get to their assigned APOE will be determined manually as well by looking at the routing of each ULN's movement on a mission. Some judgment will be used for this variable. For example, if a ULN is required to fly from Washington DC to Atlanta to onload its assigned charter mission for a flight to Korea, this will be considered reverse travel since the angle made by the two flight paths (Washington DC to Atlanta and Atlanta to Korea) was less than 90 degrees. In actuality though, a passenger that is traveling commercially from Washington DC to Korea may have to fly to Atlanta anyway for a connecting flight, but this point will be disregarded.

Actual numbers of no-shows on charter flights over the last three years will be collected from PACOM web pages created by personnel who monitored and tracked these figures for each mission during execution. This data will be in Microsoft® Excel spreadsheet format also and located on PACOM classified web pages called trackers.

These trackers show numbers of no-shows per mission by exercise as shown in Figure 4. As this data is archived annually from the web pages, much of it will have to be obtained from archives kept by J4 personnel at PACOM. Once obtained, the number of no-shows for each mission will be copied to the existing spreadsheet containing all the tabulated totals from TPFDD and variable data from before aligning actual no-shows with appropriate missions. Only unclassified data will be extracted for this research to keep the work available for the public domain.

NOTE: THIS IS A MOVEMENT TRACKER; ALL TIMES HAWAII STANDARD TIME (HST);
IF YOU HAVE QUESTIONS CALL PACOM JMC DSN XXX-XXX-XXXX **VALID AS OF: 13 XXX/0800 HST**

MSN #	SERVICE	TYPE	PAX	ACT PAX	LOAD (ST)	ACT LOAD	LAD	ARRIVE (HST)	LOCATION	DEPART (HST)	STATUS	COMMENTS
									22 XXX ARRIVALS			
TMXJ**402CG**112	MARINES	MD11	401	398	0	0	25TH		ANDERSEN	*22 XXX/0905*		
								22 XXX/1215	KADENA	*22 XXX/1536*		
								22 XXX/1945	**UTAPHAO**		**CLOSED**	
									23 XXX ARRIVALS			
LJXJ**902CG**112	MARINES	C130	34	35	0	2	25TH		IWAKUNI	*23 XXX/1209*		
								23 XXX/2028	**UTAPHAO**		**CLOSED**	
									25 XXX ARRIVALS			
TMXJ**401CG**115	ARMY	MD11	409	399	3	0	25TH		HICKAM	*24 XXX/2356*		
								25 XXX/0840	KADENA	*25 XXX/1008*		
								25 XXX/1415	**UTAPHAO**		**CLOSED**	

HST = HAWAII STANDARD TIME	**AIR DEPLOYMENT TPFDD VALIDATION:**		
NORMAL TEXT = ESTIMATED TIMES			
ITALIC TEXT = ACTUAL TIMES	**Missions Scheduled XXX**	**Missions Flown**	**XXX**
BOLD TEXT = LAST MISSION UPDATE	**PAX Scheduled XXX**	**PAX Flown**	**XXX**
	Short Tons Scheduled XXX	**Short Tons Flown**	**XXX**
	Cancelled Missions XXX	**Ridership Pax 0%**	**Stons 0 %**

Figure 4. Example No-show Tracker

As the data for this research will be gathered from several sources and is considered secondary data that has been manipulated by other people, several assumptions and limitations of the data need to be identified before analysis can be performed.

Assumptions and Limitations of Data.

The assumptions and limitations for this study regarding the data are as follows:

1. Independence of samples: Although samples will be taken over three years of exercise data and from several different exercises, many units/personnel who participate in one exercise may participate in that same exercise or other exercises in PACOM over successive years. Since these personnel may have characteristics that contribute to no-shows each time they deploy, they are essentially related and not independent of each other. However, with enough data, it will be assumed that this does not affect the overall results and independence is achieved.
2. History of Sample Data: Only the last three years worth of TPFDD data will be used for this study as databases at PACOM are archived and only the most recent data is readily available. Thus, it will be assumed that the last three years of data is a true representation of the general history of no-shows and is also useful for prediction of future no-shows. This methodology was supported by the literature review. It is prudent to think that data closer to the present is more typical of how future data will occur which is how many commercial airline companies perform their analysis as well (Freisleben, 1993; Lawrence et al., 2003; Ignaccolo & Inturri, 2000).
3. Accuracy of data: Although TPFDD data to be used for this research is secondary data and has been manipulated in some way or another by many people, it must be assumed that it was initially input and subsequently maintained accurately in databases throughout the planning and execution process. However, during actual deployment of an exercise, operations tempo for movement becomes extremely high and it is possible that last-minute required changes to the TPFDD never

actually got inputted. For actual no-show data, much of it was initially obtained from in-transit visibility systems like GTN and GDSS that reflect data put in by other command and control personnel that may or may not be accurate. However, it was known by the researcher that PACOM personnel personally made phone calls to onload locations to find out numbers of passengers that got on flights when the systems above did not appear to reflect accurate numbers. The researcher actually performed much of this data gathering while at his previous assignment and can attest to its predominantly accurate state.

4. Other changes to movement: As a caveat to assumption number three, many times changes to movement occur in the form of coordinating a passenger to move from one flight to another, but this change never gets reflected in the TPFDD. Thus, although technically the passenger may have been a no-show for one flight, they actually did show for another charter flight, and were essentially an overage for that flight. It is assumed that this occurs rarely and does not affect the overall process.

Comparison of No-show Percentage Means Between Exercises

Although the intent of this research is to build a regression model to encompass all PACOM exercises at once, initially, the data will be evaluated on an exercise-by-exercise basis to see if there are statistical differences in the percentage of no-shows between each exercise. To do this, the no-show percentages of each exercise will be compared to each other to determine if the mean rates differ. This will only be accomplished to determine if it may be better to build individual exercise prediction models instead of one model for all exercises, but regardless of outcome, a single model will be built for all PACOM exercises for this research in the hopes that the model can be used in more general terms, such as DoD wide. Before a comparison of means can be accomplished several assumptions will be made of the no-show data for each exercise, namely normality of the sample sets, independence of the sample sets, and constant variance of the sets. This will be accomplished using a statistical software package called JMP™ and the use of the Central Limit Theorem (McClave, Benson & Sincich, 1998) where appropriate. These comparison tests may show that different exercises have different no-show rates and, thus, may have different factors that relate to the dependent variable, no-shows, in various ways. If the means are statistically different using a significance level of 0.05, then it may be possible that a statistically robust model for all exercises combined may be more difficult to build.

Variable Analysis and Selection Methodology

The no-show and mission data collected on the single spreadsheet from earlier will be used to start the model building process. However, for any statistical analysis, it is important to not only do the analysis and build a model, but also to validate the findings from the analysis. This will be done by separating the data to be used for the analysis into two groups. One group will be used for building the statistical regression model and the other for testing it to see if the model can be used with reliability. Data will be randomly split into a building set that contains about 80% of the sample points and 20% for testing. To have enough data for the smaller set and still be able to make proper assumptions about normality, at least 30 sample points will be set aside, if enough are available initially, for the validation, sufficient enough for this assumption (McClave et al., 1998). To separate the sample data into two random groups, Microsoft® Excel's random number generator function will used to randomly select the required sample data points for the validation set. Once this is set aside, the large sample set will be used for the analysis portion.

Correlation analysis will be used to obtain the variables to be used for the explanatory regression model. The model will include main effects terms and possibly interaction and second-order terms of the variables used for the analysis. No terms higher than second-order will be analyzed for this study due to the increasing complexity this brings in. Initially, correlations between the independent variables, as well as all of their possible interactions and second-order terms, and the dependent variable will be performed to show the strength of the relationships between them. This will be done using JMP™ through its multivariate analysis capabilities. Positive correlations of 0.7 or more and negative correlations of -0.7 or less will be used as the initial criteria to determine whether or not to keep independent variables, or their interactions or second-order terms, for further use in a full regression model. Correlations of 0.7 or higher and -0.7 and lower are considered high by many authors (McClave et al., 1998) and thus will be used as the starting point. If the correlation analysis does not find any, or finds very few, variables with correlations of this magnitude, the highest correlating variables will be used. If this is the case, it would need to be determined how many to keep initially. McClave et al. (1998) state that the number of variables to include in the model should be significantly less than the number of sample data points while others have called for as little as one more data point than variables used (Gujarati, 1995). For this research, about 10% of the number of data points will be used as the maximum number of variables to use for a final reduced explanatory model. Since the reduced model will only include that number of variables, the initial full model should include a number more than that so that a stepwise regression technique can be used to eliminate the least contributing variables from the model. About 20% of the number of sample data points will be used as the initial number of variables to keep for the full model. There is no statistical basis for this except that this should include most, if not all, variables that correlate the highest to the number of no-shows. This will include independent variables that correlated the highest to the dependent variable, any independent variables from interaction or second-order terms that correlated highly (even if those independent variables are not highly correlated), any nominal variables that cannot be correlated due to their nature (yes or no), and finally any variables that the author judges to be significant based on the literature review and previous experience. Selection of key variables can be very subjective and the model builder may often have to use his or her own judgment in retaining possibly important variables to the model (Neter et al., 1996). Finally, the highest correlating interaction and second-order terms will be kept as well, up to 10% of the number of sample data points. In addition, any variables included in these interaction or second-order terms that were not included in the independent variables initially, will be added to the variables for the full model as stated earlier.

After the initial correlation analysis is completed, a second correlation analysis among the independent variables will be performed to determine if there are any cases of multicollinearity. Multicollinearity refers to two or more terms that may be redundant in their contribution to a model. Therefore, only one of them should be used and the others discarded from possible use as they would just add confusion to the model. This will also allow the model to remain as simple as possible. If two or more variables demonstrate a high correlation among each other of 0.8 or more or -0.8 or less, the variable that is thought to best explain the correlation relationship will be kept and the other generally discarded. This will be done by keeping the variable with the initial highest correlation to the dependent variable.

Model-Building Methodology

McClave et al. (1998) suggest one way to determine which variables to include in a final reduced model is through step-wise regression. However, a caution is given that instructs the researcher to be wary of the results of stepwise regression in making inferences about the relationship between the dependent variable and the independent variables since a large number of t-tests may need to be performed in this analysis and there is a high probability of making one or more Type I or Type II errors with this approach (McClave et al., 1998). In addition, if higher order terms are not included in the stepwise regression, this can further add to the error of determining which variables to include in the model (McClave et al., 1998). The previous correlation analysis will narrow down the number of initial variables to include in the model so that these errors are minimized when a stepwise regression is used to get the final explanatory model.

A multiple regression analysis will be used to create the final model for prediction of no-shows. The multiple regression model using the variables selected from the correlation analysis will take the form of:

$$
\begin{aligned}
E(y) = {} & \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n + \beta_{n+1} X_1 X_2 \\
& + \beta_{n+2} X_1 X_3 + \ldots + \beta_m X_{n-1} X_n + \beta_{m+1} X_1^2 \\
& + \beta_{m+2} X_2^2 + \ldots + \beta_k X_n^2 + \varepsilon
\end{aligned}
\tag{1}
$$

Where:

$E(y)$ = dependent variable of interest (response variable no-shows)
X_i = independent or predictor variables
β_i = coefficient for contribution of each independent variable towards Y
ε = random error component

McClave et al. (1999) use a popular model building process as outlined below which will be used here as well:

Step 1. Hypothesize the deterministic component of the model. This component relates the mean, E(Y), to the independent variables. This involves the choice of the independent variables to be included in the model.

Step 2. Use the sample data to estimate the unknown model parameters (β_i's) in the model.

Step 3. Specify the probability distribution of the random error term, ε, and estimate the standard deviation of this distribution, s.

Step 4. Statistically evaluate the usefulness of the model

Step 5. When satisfied that the model is useful, use it for prediction, estimation, and other purposes.

Backward step-wise regression will be the technique used to reduce the full model to a final explanatory model with just those variables that contribute statistically the most to the model. Backward stepwise regression is a technique in which all potential independent variables (those picked from the correlation analysis and those thought to be possibly significant by the researcher) and interaction terms or second-order terms of those variables are included in the initial full model. As the model is analyzed, the variables that have a statistically minimal contribution will be removed from the model. Initially, all variables, or their interaction terms or second-order terms, that have p-values greater than 0.4, according to their individual t-tests, will be removed from the model. Independent variables that have p-values higher than this but still have interaction or second-order terms that statistically contribute (below this p-value), will be kept in the models. The reduced model will then be re-run and compared to the previous model using adjusted R-squared values and an F-test to determine if the reduced nested model is statistically better or equivalent to the previous full model (McClave et al., 1998). If the reduced model is statistically equivalent or has a higher adjusted Rsquare value, the remaining variables are reassessed according to their new p-values to determine if any more contribute minimally to the model, p-value greater than 0.10, and can be removed. The new reduced model will be re-run and compared to the previous model using adjusted R-squared values and another F-test to see if this newest reduced model is statistically equivalent or better than the previous reduced model. If still equivalent or has a higher R-squared value, the newest reduced model will be reassessed again similarly until only those variables that are statistically significant, p-values less than 0.05, remain and further F-tests show that the two newest reduced models are no long statistically equivalent. The last model to be statistically equivalent to its previous model will be the final explanatory model. In addition, an overall F-test will be performed to compare this final model with the initial full model to determine if they are statistically equivalent. If this final model still retains more variables than discussed earlier as the maximum number of variables to keep, further variables may be removed despite reducing the model's overall predictive ability if it is felt that this simplifies the model.

Once the final prediction model is obtained, it will be tested and verified using the test data set removed earlier. The test data, minus the independent variable values, or number of no-shows, will be re-introduced to the build data set. Using this combined data set, the final model will be run in JMP™ to generate no-show predictions and associated prediction intervals for the dependent variables that were left out. Only those sample points that have independent data within the range of the independent data used to build the model will be used for this analysis since models are not generally useful for extrapolation as will be discusses later. Then, it will be determined if the actual number of no-shows fall within the bounds of the prediction intervals. The number of times that the actual observations fall within the individual intervals will be divided by the total number of data points used to test the model and the predictive reliability and overall robustness of the model will be calculated.

Assumptions

Some key assumptions must be made when working with multiple regression analysis. These are listed below according to McClave et al. (1999):

1. The mean of the probability distribution of the error, or ε, is zero. The average of the random error component over many experiments is zero for each independent variable.
2. The variance of the probability distribution of ε is constant

3. The probability distribution of ε is normal
4. Each value of ε associated with each value of the dependent variable is independent of all other values of ε associated with other independent variable values

Assumption 1 will be checked using residual and studentized residual plots and analyzed to see how residuals are distributed about a mean line of zero. Assumption 2 will be analyzed by visually plotting the error estimates to see if there are any abnormal patterns with the residuals. Assumption 3 will be tested visually using normal quantile plots and histograms. Assumption 4 will be checked using a Durbin-Watson test. It is doubtful that all of these assumptions will be completely satisfied, but "experience has shown that the least squares regression analysis produces reliable statistics, confidence intervals and prediction intervals as long as the departures from the assumptions are not too great" (McClave et al., 1998). In addition, with enough sample points, some assumptions such as normality are given through the Central Limit Theorem.

Additionally, the influence that each sample point has on the overall regression model will be tested using the Cook's D Influence statistic. This statistic measures overall influence, the effect of omitting a point, each point has on the estimated regression beta coefficients. Points having measurements greater than one should be examined to determine why they may be influential. This usually happens as a result of having possible mistakes made in data entry or from extreme outliers in the data (Neter et al., 1996). For this research, these measurements will be looked at and determined if they should remain in the analysis.

There may be some pitfalls associated with the regression techniques used here that need to be addressed. These include: micronumerosity, lack of sufficient data or parameter estimability problems, multicollinearity, autocorrelation, and extrapolation (McClave et al., 1998). Some of these have already been discussed earlier in the methodology, but will be grouped here again.

Micronumerosity refers to samples of data that may be too small as compared to the number of variables to be used. This was discussed earlier and criteria set to try to eliminate or minimize this problem.

Lack of sufficient data can lead to problems with key assumptions such as normality. Small sample sets of data are more difficult to work with due to possible problems with normality and not being able to invoke the Central Limit Theorem. It is estimated that enough data should be obtained from the last three years worth of exercise data to limit this problem. Also, parameter estimability occurs when there are not enough data points for the type of model being proposed. If a quadratic model is being proposed, then at least three different data points must be available to fit a curve. "In general, the number of levels of observed x values must be one more than the order of the polynomial in x that you want to fit" (McClave et al., 1998). The model for this research will only include second-order terms and thus enough sample points should be able to be collected over the last three years of exercises to negate this problem.

Multicollinearity refers to having two or more independent variables that contribute redundantly to a model. The aforementioned correlation analysis will be used to verify if there is any multicollinearity and determine if any variables should be removed from the model.

Autocorrelation is another problem that can be encountered in regression analysis. This is defined as "the correlation between time series residuals at differing points in time" (McClave et al., 1998). As discussed earlier, independence was one of the assumptions for the sample data in that data from one mission does not affect other mission data to any measurable extent. A Durbin-Watson test will be performed on the data set to check for any autocorrelation, and if any is present, the proposed model will have some uncertainty and any conclusions will be documented with that uncertainty.

Finally, extrapolation can cause problems with accuracy of the predictions from the model. Regression models should generally only be used to predict the dependent variable when independent variables are within the bounds of the original data set that was used to create the model (McClave et al., 1998). The range of the independent variables will be listed and may be a problem with the analysis of the test data. Any points not in compliance with these ranges, will not be used. As long as the limitations with extrapolation are understood by the user, it should not present a problem.

Overview of Next Chapter

Chapter 4 will present the analysis and results using the methodology described in this chapter. A comparison of means analysis will be performed first, then correlation analysis to select the variables to be used, and finally the regression model will be built. Assumptions for the regression model will then be verified and a test data set used to test the reliability of the model.

IV. Analysis and Results

Introduction

This chapter will discuss the analysis and results of this research. The analysis was conducted according to the methodology discussed in Chapter 3. The analysis of the data is used to formulate a predictive model for no-show passengers on chartered exercise passenger missions. The model will be used to show how changes in independent variables may be used to predict the output of no-shows, the dependent variable. The no-show predictions can then be used to overbook flights in order to maximize utilization of seats.

Data Analysis

Data was gathered as discussed in Chapter 3. The data is from five major CJCS exercises that occurred in the Pacific theater from late 2001 through June of 2004. These are Exercises BALIKATAN (Philippines); RECEPTION, STAGING, ONWARD MOVEMENT, AND INTEGRATION or RSOI (Korea); COBRA GOLD (Thailand); CROCODILE (Australia); and ULCHI FOCUS LENS or UFL (Korea). These exercises include a vast majority of the entire population of commercial airlift missions that were contracted for exercises in the Pacific theater by Pacific Command. Although other smaller exercises had a few charter missions, it was felt that applying a model to an exercise where only one or two charter missions were required would not change the outcome of any maximization effort. It is believed that the sample collected is a good representative sample of the entire population of exercise airlift in PACOM. In all, 106 airlift missions were collected for this research.

Initially, a comparison of the means of the no-show rates between each exercise was performed on the data. This was to determine if it was possible that a separate model for each exercise may be better than an overall model. Despite the outcome though, the author was still interested in developing an overall model that can be used elsewhere in the DoD instead of having many different models for all exercises, proving cumbersome since there are an abundance of different exercises in the DoD. To test the assumptions of normality, independence, and constant variance, JMP™ was used. Distribution and normal quantile plots done for each exercise (Appendix C, Figures 6-10) showed the data was roughly normal. Several of the exercises had very few data points which made it difficult to conclude that normality was upheld. Since the sample sets are unbalanced, constant variance is also difficult to obtain, but several tests were performed in JMP™ to reflect this assumption being valid (Appendix C, Figure 11). It was assumed that the data points within each exercise were independent of each other, although in actuality, they may not be since passengers may elect to fly on a mission other than the one they are assigned to, thus contributing to the number of no-shows on one and decreasing the number on another. It was felt that this happens fairly rarely and that this assumption could be upheld. Comparison of means tests, ANOVA and Tukey-Kramer, were performed and showed that there was a statistically significant difference in the mean no-show rates of each exercises as shown in Appendix C, Figures 12-15**.** These tests showed that the mean no-show rates for Exercises RSOI and UFL were statistically different from, and considerably higher than, Exercises COBRA GOLD and CROCODILE at an alpha level of 0.05. Exercise BALIKATAN in the Philippines fell in between and was statistically similar to both sets of exercises at an alpha level of 0.05. Having participated in each of these exercises, the researcher had made the same predictions about these exercises in that exercises in Korea generally had a higher no-show rate possibly due to a several different reasons. Korean exercises were generally not cared for as much as exercises in Australia or Thailand. Also, it is generally easier to fly commercially to Korea and obtain ground transportation to the places one needs to go to than it is in other countries due partly to U.S. military transportation and customer service available at the airports in Korea. In addition, Korean exercises use more augmentees than the other exercises since a U.S. military infrastructure is already available there and not in the other countries. Although this analysis showed that possibly separate models for each exercise could be used, care was taken in this conclusion in that two (BALIKATAN and CROCODILE), and possible three (RSOI), of the exercises had relatively small numbers of data points which may limit the validity of the analysis due to assumption of normality problems. Since the means were shown to be different and different factors may be at work for each exercise, an overall model may not be able to give the robustness that would be preferred, but will still be pursued. Further analysis by exercise may be a topic of future research, but will not be performed here.

Next, correlation analysis was conducted on the data. Before beginning this analysis, the data was split into two groups randomly as stipulated in Chapter 3 so that one group could be used to build the model and the other to validate the model. With 106 sample points, the data was split to allow for having 30 points for the validation set, leaving 76 for the model building set. With 76 sample points, the goal of having a number of variables about 10% of the number of sample data points means that the final regression model should have about eight variables. Using the model building data set, the values for the independent variables were correlated with the values for the

Table 1. Independent Variable Correlations to No-shows

Variable	No-show Correlation
No-show	1
#AD	-0.1208
#GR	0.3958
# Army AD	0.1691
# Army GR	0.3055
Tot Army	0.3278
# AF AD	0.551
# AF GR	0.3902
Tot AF	0.5927
# Joint AD	0.1355
# Joint GR	0.017
Tot Joint	0.1306
# Marine AD	-0.5202
# Marine GR	0.294
Tot Marine	-0.5024
# Navy AD	0.4591
# Navy GR	-0.0556
Tot Navy	0.4571
Sched Pax	0.2607
# Single ULNs	0.3859
# ULNs > 1	0.4956
# ULNs > 5	0.2909
# ULNs > 10	0.0388
# ULNs > 20	-0.0631
# ULNs > 50	-0.1308
# ULNs > 100	-0.3994
# ULNs > 200	-0.1426
Tot ULNs	0.4662
# Dest Diff APOD	0.3246
# Reverse Travel	0.544
# IAP	0.0981
# Ded Mil	-0.3637
# Agg Mil	0.6095
# Stops	0.3318
Length of Flight	0.3444
# Night Flight	0.2712

dependent variable to determine which were highly correlated with each other using JMP™'s multivariate analysis capabilities. A matrix of these correlations is shown in Table 1 above. All independent variables consist of numbers of scheduled passengers that fit the definition of each.

There were no correlations that met the threshold stated in Chapter 3. The lower correlations of the variables perhaps shows how the overall differences in exercises may affect the reliability of data for a combined model. Since there were no highly correlated variables, about twice the needed variables for the final model will be used for the initial full model since many of them may not contribute significantly. Using the methodology discussed in Chapter 3, about 15% of the number of sample points will be the number of variables to be included in the full model, plus additional interaction terms and second-order terms of independent variables for a total of about 25% of the number of sample points in the set. This may vary depending on the correlations of the interaction and second-order terms. Before selecting the highest correlating independent variables, the independent variables were checked for multicollinearity between them. Those that were highly correlated according to the parameters set forth in Chapter 3 were identified and are shown in Table 2.

Table 2. Multicollinearity of Variables

Variables	Correlation Coefficient
# GR – # Army GR	0.9718
# AF AD – Tot AF	0.9731
Tot Joint – # Joint AD	0.9995
Tot Joint – # Joint GR	0.8133
# Marine AD – Tot Marine	0.9976
# Navy AD – Tot Navy	0.9995
# AD – # Ded Mil	0.8452
# Single ULNs – Tot ULNs	0.9790
# Stops – Length of Flight	0.8933

In several instances, the correlations were between two sets of passenger's characteristics where one was a subset of the other, for example, the number of Air Force active duty being a subset of the total number of Air Force personnel. Therefore, the first six correlations were determined to have redundant factors, and the ones with the lowest initial correlation with the dependent variable were discarded (# Army GR, # AF AD, Tot Joint and # Joint GR, Tot Marine, and Tot Navy). The number of active duty personnel and the number loading at a dedicated military base are highly correlated possibly due to mainly active duty units using dedicated military installation APOEs whereas reserve/guard personnel being aggregated at other installations or international airports. In addition, it was felt that active duty members were more inclined to be a show for a flight than were possibly other groups of passengers such as guard/reserve personnel. Guard/reserve members are more time-constrained as discussed in the literature review and may be more inclined to acquire their own transportation despite being allocated to a charter mission. For these reasons, the number of dedicated military APOE variable will be retained and the number of active duty discarded. Next, the number of single-person ULNs was highly correlated with the total number of ULNs on a flight which makes sense since these don't fill up seats as fast as the larger ULNs. However, based on the literature review, these variables will be retained as they may be statistically significant towards predicting the number of no-shows. Finally, the number of stops was highly correlated to the length of flight. This was also intuitively obvious as typically the longer a flight is, the more stops it makes along the way for either picking up personnel or for fuel. The variable for number of stops was discarded. The new set of variables is shown in Table 3.

Table 3. Independent Variables after Multicollinearity

	No-show Correlation
#GR	0.3958
# Army AD	0.1691
Tot Army	0.3278
# AF GR	0.3902
Tot AF	0.5927
# Joint AD	0.1355
# Marine AD	-0.5202
# Marine GR	0.294
# Navy AD	0.4591
# Navy GR	-0.0556
Sched Pax	0.2607
# Single ULNs	0.3859
# ULNs > 1	0.4956
# ULNs > 5	0.2909
# ULNs > 10	0.0388
# ULNs > 20	-0.0631
# ULNs > 50	-0.1308
# ULNs > 100	-0.3994
# ULNs > 200	-0.1426
Tot ULNs	0.4662
# Dest Diff APOD	0.3246
# Reverse Travel	0.544
# IAP	0.0981
# Ded Mil	-0.3637
# Agg Mil	0.6095
Length of Flight	0.3444
# Night Flight	0.2712

From this set of variables, the ten highest correlating variables are retained for the full regression model. In addition, the variable for whether or not a flight occurred on a weekend is kept since it could not be correlated with the dependent variable due to its nominal nature, but may be important to the overall model. Finally, as pointed out earlier, the number of single-person ULNs will be kept for further analysis even though it was the eleventh highest correlated variable. These variables are shown in Table 4.

Table 4. Independent Variables for Model

	No-show Correlations
#GR	0.3958
# AF GR	0.3902
Tot AF	0.5927
# Marine AD	-0.5202
# Navy AD	0.4591
# Single ULNs	0.3859
# ULNs > 1	0.4956
# ULNs > 100	-0.3994
Tot ULNs	0.4662
# Reverse Travel	0.544
# Agg Mil	0.6095
Weekend Flight	N/A

Next, all possible interactions and second-order terms of all the original independent variables were correlated with the number of no-shows. The correlations for these are shown in Appendix D in descending order of correlation coefficient. Again, there were no correlations meeting the threshold stipulated in Chapter 3, so the ten highest correlated terms were added to the individual variables above, unless the interaction term included a variable that was discarded earlier due to multicollinearity. In these cases, the next highest correlation term was added. In addition, any independent variables included in the interaction or higher-order terms that were not in the list of variables in Table 4 were also included, despite their initial lower correlations, as required for regression analysis (McClave et al., 1998). The new list of variables is shown in Table 5.

Table 5. Independent and Interaction Terms for Model

Terms	Correlation Coefficients
# GR	0.3958
# AF GR	0.3902
Tot AF	0.5927
# Marine AD	-0.5202
# Navy AD	0.4591
# Single ULNs	0.3859
# ULNs > 1	0.4956
# ULNs > 100	-0.3994
Tot ULNs	0.4662
# Reverse Travel	0.544
# Agg Mil	0.6095
Weekend Flight	N/A
Tot AF * # Dest Diff APOD	0.6381
# Dest Diff APOD	0.3246
Sched Pax * # Agg Mil	0.6343
Sched Pax	0.2607
# Dest Diff APOD * # Agg Mil	0.6209
# Navy AD * # Reverse Travel	0.6162
Tot AF * Sched Pax	0.6157
# ULNs > 5 * # Agg Mil	0.5915
# ULNs > 5	0.2909
# ULNs > 10 * # Agg Mil	0.5851
# ULNs > 10	0.0388
# Agg Mil * Length of Flight	0.5802
Length of Flight	0.3444
# Navy AD * # Agg Mil	0.5790
# Reverse Travel * # Agg Mil	0.5772

The list in Table 5 still includes 27 different variables. This is more than was what initially desired, so the last four interaction terms and their associated independent variables that were added with them were removed, leaving 21 variables. This is close to the 25% of the sample points number discussed in the methodology chapter and should be a good basis for the initial full model relating them to the dependent variable, no-shows. The full model is shown in Equation 2 and the description of its variables given in Figure 5.

$$E(y) = \beta_0 + \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + \beta_5X_5 + \beta_6X_6 + \beta_7X_7 + \beta_8X_8 + \beta_9X_9 + \beta_{10}X_{10} + \beta_{11}X_{11} + \beta_{12}X_{12} + \beta_{13}X_{13} + \beta_{14}X_{14} + \beta_{15}X_{15} + \beta_{16}X_3*X_{13} + \beta_{17}X_6*X_{14} + \beta_{18}X_{12}*X_{14} + \beta_{19}X_5*X_{13} + \beta_{20}X_3*X_6 + \beta_{21}X_8*X_{14} \quad (2)$$

E(y) : Predicted number of no-shows

Independent Variables:
X_1 = Number of Guard/Reserve personnel scheduled for flight
X_2 = Number of Air Force Guard/Reserve personnel scheduled for flight
X_3 = Total number of Air Force scheduled for flight
X_4 = Number of Marine active duty scheduled for flight
X_5 = Number of Navy active duty scheduled for flight
X_6 = Total number of scheduled passengers on flight
X_7 = Number of 1-person ULNs scheduled for flight
X_8 = Total number of ULNs greater than 5 people on flight
X_9 = Number of ULNs greater than one person on flight
X_{10} = Number of ULNs greater than 100 people on flight
X_{11} = Total number of ULNs scheduled for flight
X_{12} = Number of personnel on flight that had a destination that was different than their APOD
X_{13} = Number of personnel that travel in reverse direction to scheduled APOE for flight
X_{14} = Number of personnel onloading at military APOEs that are used as an aggregation point where more than 25% of the personnel are from other locations

Figure 5. Full Explanatory Model

The model variables were entered into the JMP™ statistical software package to produce the analysis for the full model in Appendix E, Figure 16. The R-squared value was 0.824243 and the adjusted R-squared was 0.755894. This means that about 75% of the variance in the model is explained by the variables used and the other 25% is not. To determine how statistically useful the model is, a hypothesis test, using the F statistic, was performed and indicated the model was useful:

H_0: All β's = 0
H_a: At least one of the β's is nonzero
Test Statistic: F = 12.0592 (from Appendix E, Figure 16)
Critical value: $F_c = 1.71$ (based on k = 21, n = 76, and n-(k+1) = 54) $\alpha = 0.05$
Rejection region: $F > F_c$
Since the F-statistic exceeds the critical value, there is sufficient evidence at α = 0.05 significance level, to reject the null hypothesis and say the model is useful for predicting the dependent variable.

Even though the null hypothesis was rejected, the full model still contains too many variables, according to the requirements set forth in Chapter 3, to make it a viable solution and other variables will need to be removed to make it more parsimonious and reliable given the amount of data used to make the model. The results of the full regression model indicate that several variables could be removed (p-values greater than 0.4) to produce a reduced predictive model. The variables with β coefficients having p-values higher than 0.4 are listed in Table 6. Main effects variables whose p-values are greater than this were not be removed if they were part of an interaction term that still contributes statistically significantly to the model.

Table 6. Main Effects and Interaction Terms Reduced from Full Model

Variable	p-value
X_1	0.4309
X_8	0.7085
X_{12}	0.5374
X_3*X_{13}	0.8810
$X_{12}*X_{14}$	0.9199
X_8*X_{14}	0.8166

The reduced model was run in JMP™ again and indicated a statistically equivalent or better model than the full model (Appendix E, Figure 17) with an adjusted R-squared of 0.772807. The results of an F-test comparing these two models are shown below:

H_0: $\beta_1 = \beta_8 = \beta_{12} = \beta_{16} = \beta_{18} = \beta_{21} = 0$
H_a: At least one of these β's is nonzero
Test Statistic: F = 0.14681 (from Appendix E, Figure 18)
Critical value (F_c): $F_{6,54,0.05} = 2.34$
Rejection region: $F > F_c$
Since the F-statistic does not exceed the critical value, the null hypothesis is not rejected and the two models are statistically equivalent.

The results of the second model (Appendix E, Figure 17), indicated that still other variables could be removed to make it simpler. Variables having p-values greater than 0.10 were removed, again except for main effects terms that were part of an interaction term that contributed significantly, from the model. These variables are listed in Table 7.

Table 7. Variables Reduced from 1st Reduced Model

Variable	p-value
X_7	0.1428
X_8	0.1729
X_{11}	0.1388

A third model was developed and had an adjusted R-squared of 0.761032 (Appendix E, Figure 19). This proved to be statistically equivalent to the second model with F-test results below:

H_0: $\beta_6 = \beta_7 = \beta_{11} = 0$
H_a: At least one of these β's is nonzero
Test Statistic: F = 1.86013 (from Appendix E, Figure 20)
Critical value (F_c): $F_{3,62,0.05} = 2.76$
Rejection region: $F > F_c$
Since the F-statistic does not exceed the critical value, the null hypothesis is not rejected and the second and third models are statistically equivalent.

Further analysis shows that another variable could be removed to possibly make the model even simpler. Using a p-value threshold of 0.10 again, variable X_{10}, with p-value = 0.5289, was removed. A fourth model was developed in JMP™ (Appendix E,

Figure 21) and had an adjusted R-squared of 0.763269. The results of the F-test comparing the fourth model to the third are listed below:

H_0: $\beta_{10} = 0$
H_a: β_{10} not equal to zero
Test Statistic: F = 0.40090 (from Appendix E, Figure 22)
Critical value (F_c): $F_{1,66,0.05} = 3.99$
Rejection region: $F > F_c$
Since the F-statistic does not exceed the critical value, the null hypothesis is not rejected and the second and third models are statistically equivalent.

Again, analysis showed that one more term could be removed to possibly reduce the model further using a threshold p-value of 0.05. This was the interaction term between the total number of Air Force personnel and the total number of scheduled passengers on the flight. A fifth model was run in JMP™ (Appendix E, Figure 23) having an adjusted R-squared of 0.75372. Results of the F-test comparing this model to the fourth model are listed below:

H_0: $\beta_{20} = 0$
H_a: β_{20} not equal to zero
Test Statistic: F = 3.6217 (from Appendix E, Figure 24)
Critical value (F_c): $F_{1,67,0.05} = 3.99$
Rejection region: $F > F_c$
Since the F-statistic does not exceed the critical value, the null hypothesis is not rejected and the second and third models are statistically equivalent.

A final review of the rest of the variables shows that each variable is statistically significant to the predictive ability of the model (all p-values < 0.05) at a significance level of 0.05. Thus, no more variables will be removed and this fifth model will be the final reduced model. The final model was compared to the initial full model and validated that they were statistically equivalent to each other using the following F-test:

H_0: $\beta_1 = \beta_6 = \beta_7 = \beta_8 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{16} = \beta_{18} = \beta_{20} = \beta_{21}$
Ha: All β's not equal to zero
Test Statistic: F = 0.05784 (from Appendix E, Figure 25)
Critical value (F_c): $F_{13,54,0.05} = 1.92$
Rejection region: $F > F_c$
Since the F-statistic does not exceed the critical value, the null hypothesis is not rejected and the final reduced and full models are statistically equivalent.

Prior to using the model to predict numbers of no-shows, the assumptions of normality, constant variance, and independence were tested. The assumption of normality of the error (using residuals and studentized residuals) was tested by plotting them in a distribution chart and creating a normal quantile plot on each (Appendix E, Figure 26). The plots revealed a normal distribution for both.

The assumption of constant variance of the error was tested visually by plotting the residuals against the predicted values which showed no patterns in the data, although a couple of points appeared to be potential outliers. A linear plot of the error estimates in the order given also showed constancy and failed to demonstrate any abnormal patterns of the variance (Appendix E, Figure 27).

The independence of each of the errors was tested using the Durbin-Watson test (Appendix E, Figure 23). Even though the data is not necessarily time series data in that points are taken in equal increments of time, the points are one after another in time and the test was performed. The results showed that there is no autocorrelation with $d \approx 1.97$ whereas a value of two shows independence.

Finally, the influence of each data point on the model was analyzed using the Cook's D Influence statistic. The plot of the Cook's D statistic (Appendix E, Figure 28) showed that though some points were more influential than the rest, they were not significant enough, greater than one, to be removed.

Final Model Results

The final explanatory model that is about 75% predictive of no-shows on exercise charter airlift is shown below in Equation 3 with description of its variables below:

$$E(y) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_5 * X_7 + \beta_{10} X_4 * X_6 \qquad (3)$$

Dependent Variable

$E(y)$: Predicted number of no-shows

Independent Variables:

X_1 = Number of Air Force Guard/Reserve personnel scheduled for flight
X_2 = Total number of Air Force scheduled for flight
X_3 = Number of Marine active duty scheduled for flight
X_4 = Number of Navy active duty scheduled for flight
X_5 = Total number of scheduled passengers on flight
X_6 = Number of personnel that travel in reverse direction to scheduled APOE for flight
X_7 = Number of personnel onloading at military APOEs that are used as an aggregation point where more than 25% of the personnel are from other locations
X_8 = Flight scheduled on a weekend (Friday 1800 – Sunday 2359)

The model is only good for practical use for independent variables that fall within the data set limits used to build the model as shown in Table 8.

Table 8. Range of Independent Variables

Variable	Min	Max
X_1	0	79
X_2	0	319
X_3	0	409
X_4	0	99
X_5	120	420
X_6	0	140
X_7	0	409
X_8	0	1

The beta parameters for each of the variables in the final model are found in Table 9.

Table 9. Beta Parameters for Final Model

Beta Parameter	Value
β_0	-8.445298
β_1	-0.69982
β_2	0.3254449
β_3	-0.076768
β_4	0.439369
β_5	0.1381863
β_6	0.3717535
β_7	0.031726
β_8	-8.995767
β_9	0.0012832
β_{10}	0.0115661

To analyze the robustness, or predictive ability, of the final model, the independent variable data from the randomly selected test data set was used. The test set data was integrated back into the build data set to form the whole sample data set again, except for the dependent variable values from the test set. The final model was then re-run with the complete data set to produce predicted responses and associated prediction intervals, at 95% significance level, for the test set individual missions. The actual number of no-shows from these historical missions was then compared to the prediction intervals obtained to determine if they fell within that range (Appendix F, Table 13). Of the 30 points used for the test set, three of them contained independent variable values than fell outside the range of the values that were used to build the model and had to be removed from the analysis. Of the other 27 points tested, 26 of them, or 96.3%, fell within the prediction intervals computed. Since roughly 95% should fall within the intervals, the model appeared to have good predictive reliability at about 96%. However, as three of the missions had to be eliminated from the test set due to variable values falling outside the range that the model was built with, additional data would have been helpful to increase these ranges for better practical use in the field.

Overview of Next Chapter

Chapter 5 will state the conclusions of this research effort. The research questions posed in Chapter I will be answered. Next, some recommendations for use of the prediction model created will be made. Finally, some of the research limitations will be explained and some recommendations for future research will be suggested.

V: Conclusions

Introduction

This chapter discusses the conclusions drawn from the research. Each of the research questions will be addressed and some implications will be discussed. Next, areas of possible further research will be suggested.

Findings

This section answers the investigative and research questions presented in Chapter I. The first four investigative questions are answered from information collected and analyzed in the literature review. The answers to questions five through seven are answered by a combination of information in the literature review and the analysis done in Chapter 4.

Investigative question 1. What are the costs associated with no-shows?

As discussed in the literature review, missions for exercises are primarily one-way to carry passengers to the exercise and then later, separate contracted missions are run to move personnel back, again one-way. The average cost per seat as discussed in the literature review was given as about $1,100. The analysis in Chapter 4 showed that the average no-show rate for the missions utilized in this research was 15.46%. This is close to the rate that was given by the GAO report done over 20 years ago (GAO, 1983). For all the exercise airlift data used for this research over a period of three years, a total of 33,942 passengers were scheduled to fly on charter airlift. Of that, 28,693 showed for their flight, meaning there were 5,249 no-shows. At $1,100 per seat, this equates to about $5.7 million, or $1.9 million per year. That's roughly about five charter missions that were bought annually that could have been saved by filling empty seats with other personnel. Although it is not certain that overbooking missions and consolidating passengers could have been done effectively, there is still a potential for extensive savings by applying the model proposed by this research to predict empty seats and fill them through overbooking. In addition to the cost of empty seats, if the passengers that were no-shows for the charter missions also purchased commercial tickets to get them to the exercise using unit funds, the cost effectively doubles. This second cost, unfortunately, would still remain as there would still be the same number of no-shows. This research did not look at the specific causes for no-shows, and thus makes no inference to saving any of these possible additional costs.

Investigative Question 2. How are chartered exercise passenger missions planned for and how may this contribute to no-shows for missions?

As the literature review pointed out, there are several variables that may have an impact on the number of no-shows a mission may have. The planning process may inadvertently introduce some of these variables. It was noted that planning movement windows and APOEs and APODs may have a correlational relationship with the number of no-shows on any given mission. These parameters are decided during the planning process. If it is known that scheduling a flight over a weekend contributes significantly to the number of no-shows, then planners could ensure that planning windows do not encompass a weekend. This research showed that planning over a weekend did have an impact on the number of no-shows. There tended to be more no-shows for missions on the weekend than during the weekdays. In addition, if a certain type of APOE is used as an onload location, this may have a higher correlation with the number of no-shows than another type of APOE. Again, it was shown that as the number of passengers onloading at an aggregate APOE goes up, the number of no-shows generally went up as well. The planners could then incorporate this into the planning process as much as possible to try to influence a reduction in no-shows. The model's predictive ability is fairly good, but there is obviously still some variability in it. These planning variables could be controlled somewhat by the planners at planning conferences and during the TPFDD building stages before validation. During this time, the prediction model could be used to try to overcome the effects of the variables through overbooking missions in hopes that the number of predicted no-shows will match actual no-shows in order to utilize as many seats as possible.

Investigative question 3. How does the commercial airline industry model no-shows and can this be used to address the military's problem?

Although commercial flights and military charter flights are similar in some ways, there appeared to be a significant difference in how to model no-shows for each. The commercial airline industry utilizes models mainly for yield management, but does look at some of the same flight characteristics that were included in the research for military charter no-shows. The commercial airlines analyze particular routes and times of flights over an annual basis to model no-shows. Certain routes during different times of the day or days of the week may prove to have a bigger influence over the number of no-shows than other routes and times for these models. These factors were incorporated into this research as well as discussed in the literature review. In particular, whether a flight occurred on a weekend or not played a significant role in the explanatory model. In contrast to military charters, the commercial airlines are able to collect much more data to model their operations, possibly allowing for more accuracy in their models. Over a period of three years for this research, only 106 flights were used, whereas for commercial airlines hundreds of thousands of flights over the course of a year can be analyzed. This data advantage gives the commercial models more robustness.

Except for one study found which looked at passenger characteristics (Lawrence et al., 2003), commercial airlines and researchers studying them did not use passenger characteristics such as gender, age, socio-economic status, or job status, to name a few, as part of their models. Several of these types of variables, such as military service and active duty/reserve status, were used for the final model in this research. Generally, the main elements used in commercial airline models were fare class and booking lead time whereas these parameters are not a factor for military charters.

Investigative question 4. Are there other industries with no-show problems with appropriate models that could be used to predict military airlift no-shows?

The other industries looked at in this research were the restaurant, hotel, and healthcare industries primarily. Whereas the restaurant and hotel industries were interested in determining possible numbers of no-shows based on business factors such as days of the week or times of day, the healthcare industry looked at not only determining who the no-shows were, but also implementing programs to keep no-shows from occurring in the first place. Although this will be discussed later in these conclusions as a possible future endeavor for military airlift research, this study did not investigate methods for determining why there are no-shows. In general, these other commercial industries had no-shows just as military charter airlift does, Some of the same factor analysis was used from these industries such as determining if times of the day or days of the week could have a relationship to the number of no-shows. No actual statistical models were available to be studied for these industries, but the qualitative research available in these areas did provide insight into possible additional studies that could be performed for military airlift.

Investigative question 5. Historically, what have no-show rates been and are they a concern for commanders?

The research showed that, for the data gathered, an overall no-show rate of 15.46% was observed over the last three years for the exercise charter airlift sampled. In addition, the literature review showed that no-show rates on commercially chartered airlift was roughly the same as far back as the early 1980s. As one can imagine, this is of particular concern for commanders, especially combatant commanders, who are paying for this airlift resource that is not being fully utilized due to no-shows. In addition, commercial airlift is often in short supply due to competing priorities such as contingency operations and higher priorities than exercise airlift. Commanders work with ever-decreasing exercise budgets and any waste of those budgets can become critical to obtaining required training. During the researcher's time working at PACOM, a great deal of time was spent on collecting no-show data to determine who the no-shows were so that the PACOM commander could address the problem to his individual component commanders as well as commanders from other unified commands or headquarters. In the meantime, airlift planners worked on ways to overcome no-show problems by using their own judgment in overbooking missions trying to second-guess the amount of no-shows in order to maximize utilization of seats. The model produced by this research is a first step toward helping in this effort and any further research looking at additional variables in an explanatory model could continue to improve on this.

Investigative question 6. Do passenger characteristics such as branch of service or reserve/active duty status have a relationship with higher or lower numbers of no-shows?

The research showed that characteristics such as branch of service and to some extent, guard/reserve or active duty status, does have a statistically significant relationship with the number of no-shows on a charter mission. It was found that eight different variables could be used to show a relationship to the number of no-shows, five of them being passenger-specific variables. One of those variables was whether or not a passenger had to travel in a reverse direction from their final destination in order to get to their APOE. Although not a variable that describes a personal characteristic of a passenger, it does describe something they have to do before they enter the strategic airlift system, and was important in the final model. One passenger characteristic that was originally thought would have an influence on the number of no-shows was the size of the ULN that passengers belong to. This ended up not having enough statistical significance to stay in the final model.

In addition, as all of the variables used in the final model were not particularly highly correlated to the number of no-shows, as found in the correlation analysis in

Chapter 4, other variables from the research may have possibly been used to build a model somewhat equivalent to this one. It is felt though, that the model produced was the best possible one with the variables initially explored for this research.

Investigative question 7. Do passenger mission characteristics such as APOEs/APODs used, number of stops or flying time of missions, departure days or times, total number of scheduled passengers for a mission, or exercise location have a relationship with number of no-shows?

Mission specific factors did have some significance in the final model for this research. In particular, factors for total number of scheduled passengers on a mission, number of passengers scheduled to onload at a certain type of APOE, and whether the flight occurred on a weekend had a significant relationship to the number of no-shows. The number of passengers that were scheduled to onload at a military base primarily used as an aggregation point was the only significant factor among three types of APOEs. It may seem obvious that the number of no-shows would go up as the total number of passengers scheduled for a flight goes up, but this was one of the lowest correlated variables in the model. This possibly shows that other factors have a significant role as well and that scheduled passengers may interact with some of them. This did occur in one of the interaction terms used for the explanatory model.

Although exercise location was originally included as a factor for this research, it was decided that in order to find a model that could be used and improved on in further research, this factor would not be analyzed. However, to determine if the exercise may have an influence on the number of no-shows, each exercise was compared to each other to see if the mean number of no-shows were statistically different and may have an affect on the robustness of an all-encompassing model. It appears that this may be the case.

Significance of Research

The overall robustness of the model was not as good as the researcher had hoped, but did provide a viable first step towards other research. The predictive reliability was high at 96.3%, but the variability could still be refined. The model looked at numerous passenger and mission related variables to try to predict numbers of no-shows. Despite its limitations, the model could be used by planners throughout the DoD as a guiding tool in making decisions on planning airlift. Airlift planners can use it as a first step in deciding how to plan for exercises and finally how to execute charter missions. However, as this is just a tool, the planner will still need to make key decisions based on experience and other variables. For instance, no-shows may be higher during periods of other heavy contingency deployments going on and a planner may have to use his or her own judgment in planning missions based on what has happened in other similar exercises during times of heavy operations tempo. As stated earlier, the model in its current form can be used to give the planner some insights into the planning process that could potentially save the PACOM commander, and therefore the DoD, up to a couple million dollars a year. Further refinement of the model on a DoD perspective could save even more money.

Recommendations for Action and Further Research

Although this study produced a moderately effective model to predict no-shows for exercise charter airlift, there were several limitations to it. As this research used only quantitative data found in historical databases, the factors used at obtaining the final model were limited in scope. The specific causes of no-shows were not investigated and a much more valuable objective would be to research why passengers do not show up for their flights, and then try to overcome those barriers found. As stated in the literature review, there may be three basic reasons why people do not show up for their flights: intentional, inadvertent, and unavoidable circumstances. By focusing on these three primary causes for no-shows, additional research could produce a model and perhaps training techniques to be used DoD-wide for decreasing the number of no-shows. In order to do that, a more extensive research project could be performed through surveying of a large sample of units from all services of the military to determine why people miss their flights. It is felt that many no-shows are caused by intentional (possibly through ignorance of the mobility system) reasons such as units just wanting to try to take care of their personnel better by buying their own tickets to exercises. Quality of life issues have been a major influence in many programs the military has been pursuing over the last several years. Charter flights are not necessarily the most convenient or most timely ways of flying, but they are best for the overall effectiveness of military training, and thus for wartime requirements.

Since the amount of data was limited in this research to only 106 sample points, additional data could have provided for a more robust model with narrower predictability. This was felt to be one of the greatest limitations of this research and further collection of data either from additional years of missions, or from other combatant commands could make this model more useful.

It was also felt that the mobility process may break down in the communication of airlift assignments down to the unit level. Units may have a difficult time seeing what missions have been assigned to their personnel due to complexity of accessing classified computer systems, or they may just not understand the mobility system and what to look for when trying to determine how their personnel should be traveling to an exercise. It is the author's experience that many military personnel do not even understand the basic unit of contingency or exercise movement which is the Unit Line Number, or ULN. The author has received many phone calls from personnel tasked to deploy to an exercise, but when asked what their ULN was to cross-reference it to an assigned mission, they did not know. Additional research on this problem could be performed to see how widespread this may be and propose possible solutions to fixing it. As this would be a tremendous undertaking by any single research project, it could be pursued on an individual service (Army, Air Force, etc.) level. In addition, it was thought that there may be significance to whether a deployer was a reserve or guard member, even though the final prediction model found here does not utilize that factor. Further study on the difference between active duty units and Guard/Reserve units could be performed. And even though the model proposed by this research did contain a factor for Air Force Guard/Reserve personnel, other models could be produced with other Guard/Reserve factors for the other services.

Additionally, this study did not research unavoidable circumstances leading to no-shows. One obvious factor that could lead to some no-shows is for passengers that must fly to their APOE to meet a charter and are delayed by weather or possible other circumstances. It was assumed that weather did not play a major role in the no-show data that was obtained for this research and did not affect the overall outcome of this research. The data collected for this research was from exercises occurring between the March to September timeframe, predominantly a timeframe with good weather. However, even summer thunderstorms or winds can delay travelers. Also, mechanical problems, not only with flying, but also with driving to an APOE can affect the number of no-shows. It is felt that this factor is not a substantial factor in determining no-shows, but further research could be performed to see how much of an influence this has.

Another factor not studied here was the rank of an individual as it was not available from TPFDD information. It is possible that many no-shows may be related to the rank of a passenger. There may be a high correlation among the number of no-shows and someone's rank. Generally, the higher ranking an individual is, the more valuable their time is, either for attending critical meetings or other work-related duties. Higher ranking personnel may then intentionally book other means of transportation as the charter may not meet their needs as far as timing is concerned. Further analysis on determining who actual no-shows are for charter flights could be conducted to see what ranks predominantly miss their flights, if there is a relationship. In addition, further analysis could be conducted to compare unit-level personnel to headquarters-level personnel.

It is evident that this research has not covered all the possible factors in determining the number of no-shows, and no model would ever be able to predict no-shows with absolute accuracy, but additional factors could be presented to strengthen this research. As time was a limiting factor in developing this research effort, more extensive research could be conducted to determine other more prominent factors through surveys of large samples of exercise participants in determining possible reasons they did or did not utilize the charter airlift that was assigned to them. Research of this sort would have to be done carefully and possibly anonymously, as naming actual no-shows by name or unit could lead to discipline actions which would severely bias the research. This research would have a cost involved with it as well. The researcher would most likely have to travel to individual exercises to collect this data while it is happening or work very closely with others in collecting it. A delay in collecting personal or professional thoughts on why someone missed a flight has the potential to change the outcome of the responses.

As this research only used data from major exercises in the PACOM area of responsibility, one cannot make an inference that the explanatory model built here is generalizeable over all charter passenger airlift for the DoD. In general, though, each combatant commander proceeds in the same manner for exercise airlift planning and, thus, one would expect the model developed here, in some form, to work for other DoD exercises and perhaps even contingency missions. However, further research would be required to establish this generality. Additional research could continue to remain limited to just joint exercises or be opened up to service-specific exercises. It is felt that joint and service-specific exercises are two entirely different categories though and should probably be dealt with separately initially. However, contingency airlift could be studied using the same methodology, as the same planning and execution process is used for this process, albeit, generally at a little faster pace. This could create additional factors for no-shows such as length of time between validation of a requirement and actual airlift movement.

No-shows can be a great burden on airlift efficiency for exercises, unit movements, daily channel moves, and contingency or wartime movements. With the amount of money that could stand to be saved by either implementing programs to try to eliminate no-shows, or at least minimize them, or to use a model to predict no-shows and overcome them with overbooking techniques, this research and further recommended research could be very valuable to the DoD. With a possible cost savings in PACOM alone of over $5 million over three years, an overall DoD savings could reach tens of millions of dollars. Although not much in the overall scheme of the DoD budget, this a considerable amount of money that could be used for other important requirements for combatant commanders.

Appendix A: Variables

Dependent variable:

Y = Number of no-shows for each flight

Table 10. Independent variables:

Variable Name	Variable Definition
# AD	Number of Active Duty personnel scheduled for flight
# GR	Number of Guard/Reserve personnel scheduled for flight
# Army AD	Number of Army Active Duty personnel scheduled for flight
# Army GR	Number of Army Guard/Reserve personnel scheduled for flight
Tot Army	Total number of Army personnel personnel scheduled for flight
# AF AD	Number of Air Force Active Duty personnel scheduled for flight
# AF GR	Number of Air Force Guard/Reserve personnel scheduled for flight
Tot AF	Total number of Air Force personnel personnel scheduled for flight
# Joint AD	Number of Joint Active Duty personnel scheduled for flight
# Joint GR	Number of Joint Guard/Reserve personnel scheduled for flight
Tot Joint	Total number of Joint personnel personnel scheduled for flight
# Marine AD	Number of Marine Active Duty personnel scheduled for flight
# Marine GR	Number of Marine Guard/Reserve personnel scheduled for flight
Tot Marine	Total number of Marine personnel personnel scheduled for flight
# Navy AD	Number of Navy Active Duty personnel scheduled for flight
# Navy GR	Number of Navy Guard/Reserve personnel scheduled for flight
Tot Navy	Total number of Navy personnel scheduled for flight
Sched Pax	Total number of Scheduled Passengers for flight
# Single ULNs	Number of Single-person ULNs scheduled for flight
# ULNs > 1	Number of multiple-person ULNs scheduled for flight
# ULNs > 5	Number of ULNs containing more than 5 people scheduled for flight
# ULNs > 10	Number of ULNs containing more than 10 people scheduled for flight
# ULNs > 20	Number of ULNs containing more than 20 people scheduled for flight
# ULNs > 50	Number of ULNs containing more than 50 people scheduled for flight
# ULNs > 100	Number of ULNs containing more than 100 people scheduled for flight
# ULNs > 200	Number of ULNs containing more than 200 people scheduled for flight
Tot ULNs	Total number of ULNs scheduled for flight
# Dest Diff APOD	Number of personnel who have different destinations than scheduled APOD
# Reverse Travel	Number of personnel who had to travel in a reverse direction from

	their APOD to get to their APOE
# IAP	Number of personnel onloading at an international airport as their APOE for a flight
# Ded Mil	Number of personnel onloading at a military base selected as a dedicated APOE for over 75% of the scheduled passengers being from that base
# Agg Mil	Number of personnel onloading at a military base selected as an aggregation point for over 25% of the personnel not from that base
# Stops	Number of scheduled stops for the mission
Length of Flight	Length of Flight in hours
# Night Flight	Number of personnel scheduled to onload at night for a flight (aircraft departs between 1800 and 0600)
Weekend Flight	Nominal variable: does flight leave on a weekend (aircraft departing between 1800 Friday and 2359 Sunday)

Appendix B: CRAF Statistics

Table 11. CRAF Participation (Schmidt 1997)

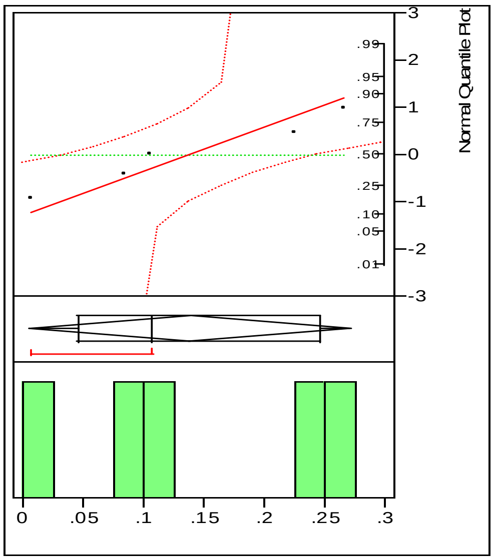
Location (Operation)	Year	Number of Flights	Pax Delivered
Vietnam War	1964	n.a	11,436,165
Panama (Just Cause)	1989	12	2,929
Persian Gulf (Desert Shield/Desert Storm	1990	3,604	405,448
Philippines (Fiery Vigil)	1991	68	16,882
Northern Iraq (Provide Comfort	1991	172	18,294
Former Soviet Union (Provide Hope)	1992	82	100
Bosnia (Provide Promise)	1992	36	2,345
Somalia (Restore Hope)	1992	234	52,136
Rwanda (Support Hope)	1994	65	548
Cuba (Sea Signal V)	1994	214	29,524
Panama (Panama Haven/South Haven)	1994	24	4,647
Haiti (Phoenix Shark)	1994	141	33,546
Cuba (Safe Haven/Safe Passage)	1994	27	4,050
Persian Gulf(Vigilant Warrior)	1994	119	12,010
Bosnia (Joint Endeavor)	1995	534	41,333

Appendix C: Comparison of Exercise No-show Means

Exercise=BK

Distributions

No-show %



Quantiles

100.0%	maximum	0.26738
99.5%		0.26738
97.5%		0.26738
90.0%		0.26738
75.0%	quartile	0.24679
50.0%	median	0.10714
25.0%	quartile	0.04714
10.0%		0.00833
2.5%		0.00833
0.5%		0.00833
0.0%	minimum	0.00833

Moments

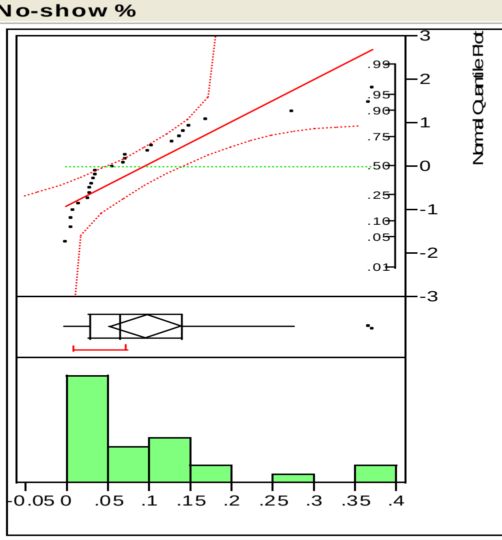
Mean	0.1389968
Std Dev	0.1060516
Std Err Mean	0.0474277
upper 95% Mean	0.2706773
lower 95% Mean	0.0073163
N	5

Figure 6. Exercise Balikatan Distribution

Exercise=CG

Distributions

No-show %



Quantiles

100.0%	maximum	0.37387
99.5%		0.37387
97.5%		0.37387
90.0%		0.30382
75.0%	quartile	0.14042
50.0%	median	0.06564
25.0%	quartile	0.02991
10.0%		0.00806
2.5%		0.00000
0.5%		0.00000
0.0%	minimum	0.00000

Moments

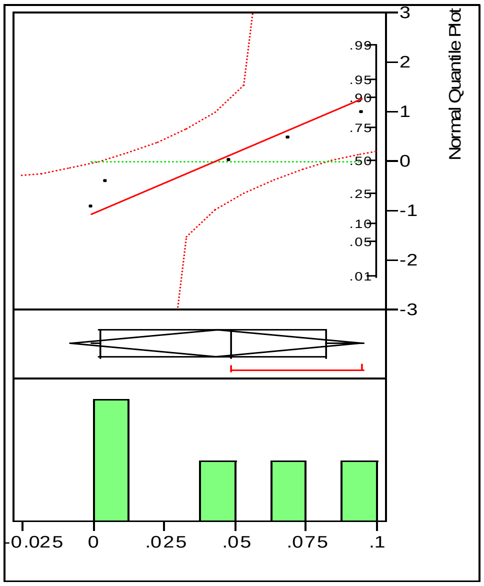
Mean	0.0969913
Std Dev	0.1034661
Std Err Mean	0.0202914
upper 95% Mean	0.1387821
lower 95% Mean	0.0552004
N	26

Figure 7. Exercise Cobra Gold Distribution

Exercise=CROC

Distributions

No-show %



Quantiles

100.0%	maximum	0.09509
99.5%		0.09509
97.5%		0.09509
90.0%		0.09509
75.0%	quartile	0.08218
50.0%	median	0.04870
25.0%	quartile	0.00253
10.0%		0.00000
2.5%		0.00000
0.5%		0.00000
0.0%	minimum	0.00000

Moments

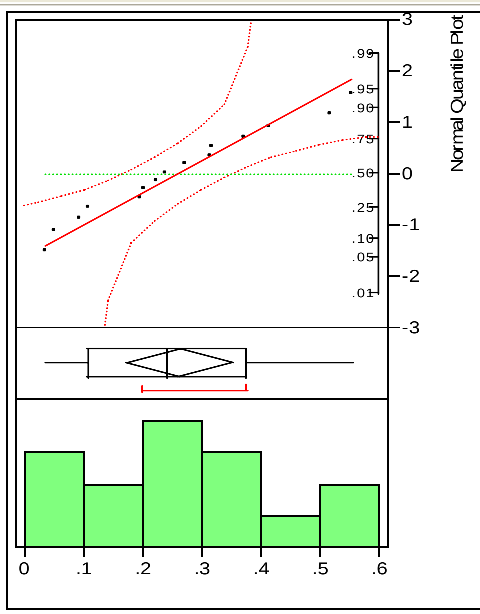
Mean	0.0436242
Std Dev	0.0409993
Std Err Mean	0.0183355
upper 95% Mean	0.0945316
lower 95% Mean	-0.007283
N	5

Figure 8. Exercise Crocodile Distribution

Exercise=RSOI

Distributions

No-show %



Quantiles

100.0%	maximum	0.55486
99.5%		0.55486
97.5%		0.55486
90.0%		0.53394
75.0%	quartile	0.37545
50.0%	median	0.24225
25.0%	quartile	0.11006
10.0%		0.04619
2.5%		0.03788
0.5%		0.03788
0.0%	minimum	0.03788

Moments

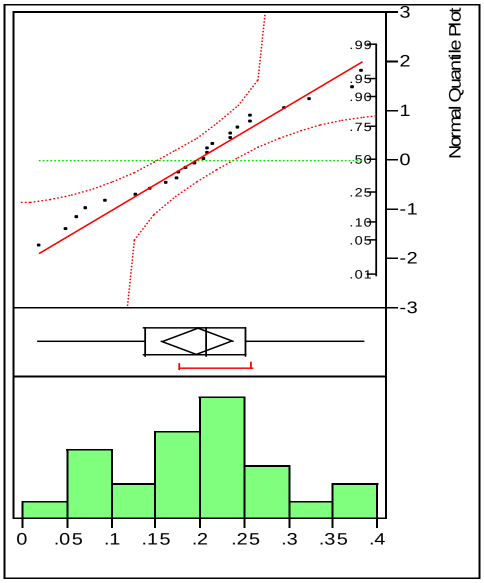
Mean	0.2628828
Std Dev	0.1582214
Std Err Mean	0.0408526
upper 95% Mean	0.3505028
lower 95% Mean	0.1752627
N	15

Figure 9. Exercise RSOI Distribution

Exercise=UFL

Distributions

No-show %



Quantiles

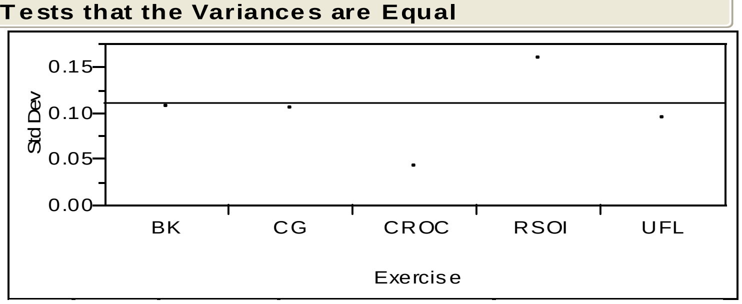
100.0%	maximum	0.38442
99.5%		0.38442
97.5%		0.38442
90.0%		0.34522
75.0%	quartile	0.25235
50.0%	median	0.20795
25.0%	quartile	0.13871
10.0%		0.05873
2.5%		0.02111
0.5%		0.02111
0.0%	minimum	0.02111

Moments

Mean	0.1982514
Std Dev	0.0938771
Std Err Mean	0.0187754
upper 95% Mean	0.237002
lower 95% Mean	0.1595008
N	25

Figure 10. Exercise UFL Distribution

Tests that the Variances are Equal



Level	Count	Std Dev	MeanAbsDif to Mean	MeanAbsDif to Median
BK	5	0.1060516	0.0862306	0.0841009
CG	26	0.1034661	0.0766384	0.0711224
CROC	5	0.0409993	0.0328791	0.0359789
RSOI	15	0.1582214	0.1250191	0.1247743
UFL	25	0.0938771	0.0713368	0.0710683

Test	F Ratio	DFNum	DFDen	Prob > F
O'Brien[.5]	2.1538	4	71	0.0830
Brown-Forsythe	2.0032	4	71	0.1033
Levene	2.3804	4	71	0.0596
Bartlett	2.4905	4	.	0.0411

Warning: Small sample sizes. Use Caution.

Welch Anova testing Means Equal, allowing Std Devs Not Equal

F Ratio	DFNum	DFDen	Prob > F
10.8587	4	17.917	0.0001

Figure 11. Test for Constant Variance

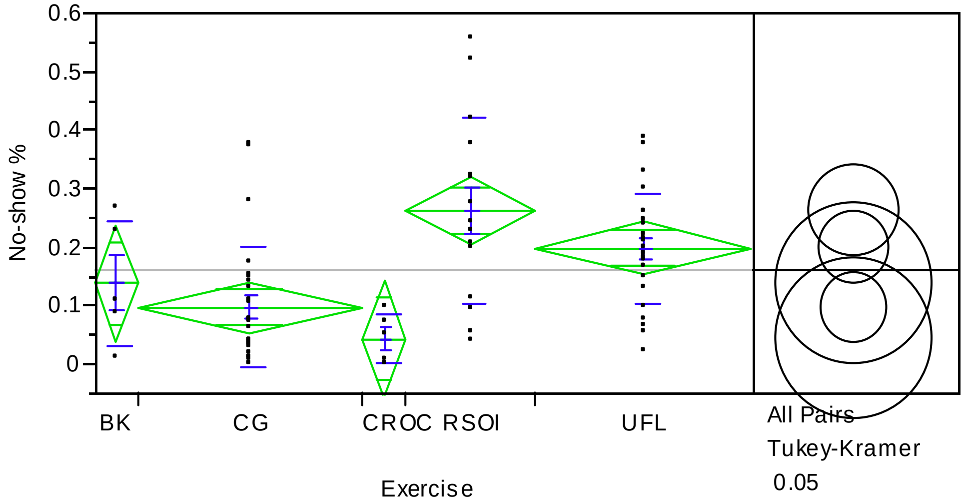


Figure 12. Test for Equal Means

Analysis of Variance

Source	DF	Sum of Square:	Mean Square	F Ratio	Prob > F
Exercise	4	0.3680968	0.092024	7.4135	<.0001
Error	71	0.8813282	0.012413		
C. Total	75	1.2494250			

Figure 13. ANOVA Test of Means

Means for Oneway Anova

Level	Numbe	Mean	Std Error	Lower 95%	Upper 95%
BK	5	0.138997	0.04983	0.0396	0.23835
CG	26	0.096991	0.02185	0.0534	0.14056
CROC	5	0.043624	0.04983	-0.0557	0.14297
RSOI	15	0.262883	0.02877	0.2055	0.32024
UFL	25	0.198251	0.02228	0.1538	0.24268

Std Error uses a pooled estimate of error variance

Figure 14. Means of No-shows for Exercises

Level			Mean
RSOI	A		0.26288276
UFL	A		0.19825141
BK	A	B	0.13899677
CG		B	0.09699128
CROC		B	0.04362419

Levels not connected by same letter are significantly diffe

Figure 15. No-show Means Comparison

Appendix D: Interaction Correlations

Table 12. Interaction Correlations to No-shows

Interaction Term	Correlation
No-show	1
Tot AF * # Dest Diff APOD	0.6381
Sched Pax * # Agg Mil	0.6343
# Dest Diff APOD * # Agg Mil	0.6209
# Navy AD * # Reverse Travel	0.6162
Tot AF * Sched Pax	0.6157
Tot Navy * # Reverse Travel	0.6156
# Agg Mil	0.6121
# AD * # Reverse Travel	0.5984
Tot AF	0.595
# ULNs > 5 * # Agg Mil	0.5915
# AD * # Agg Mil	0.5881
# ULNs > 10 * # Agg Mil	0.5851
# AF AD * # Dest Diff APOD	0.5809
# Agg Mil * Length Flight	0.5802
Tot Navy * # Agg Mil	0.5793
# Navy AD * # Agg Mil	0.579
# Reverse Travel * # Agg Mil	0.5772
# ULNs > 5 * Tot ULNs	0.5766
# ULNs > 1 * # Agg Mil	0.576
Tot Army * # Navy AD	0.5751
Sched Pax * # Reverse Travel	0.5751
Tot Army * Tot Navy	0.5739
# AF AD * Sched Pax	0.5737
# ULNs > 1 * # Dest Diff APOD	0.5681
Tot AF * # ULNs > 5	0.5672
Tot AF * # ULNs > 1	0.5641
# ULNs > 20 * # Agg Mil	0.5636
# Navy AD * # ULNs > 5	0.5635
# Dest Diff APOD * # Reverse Travel	0.5623
Tot Navy * # ULNs > 5	0.5613
Tot Marine * # Agg Mil	0.5604
# Agg Mil * # Stops	0.5598
# ULNs > 1 * # Night Flight	0.5573
# Agg Mil^2	0.5568
# Agg Mil * # Night Flight	0.5553
# AD * Tot AF	0.5539
# AF AD	0.5533
# AD * # GR	0.5525
Tot AF * # ULNs > 10	0.5465
# ULNs > 1 * Length Flight	0.5448

# Navy AD * # ULNs > 1	0.5443
Tot Navy * # ULNs > 1	0.5429
# Reverse Travel	0.5384
# Reverse Travel * Length Flight	0.5379
#GR * Tot AF	0.5377
Tot ULNs * # Reverse Travel	0.5333
# AF AD * # ULNs > 1	0.5329
Tot AF * # Reverse Travel	0.5312
# ULNs > 1 * # Reverse Travel	0.5307
Tot Army * Tot AF	0.5274
# ULNs > 1 * Tot ULNs	0.5268
# Navy AD * # Dest Diff APOD	0.526
Tot ULNs * # Agg Mil	0.5234
Tot Navy * # Dest Diff APOD	0.5225
# Reverse Travel * # Stops	0.5222
Tot AF^2	0.5215
# AF AD * # Reverse Travel	0.5166
# AD * # AF AD	0.5152
# GR * # AF AD	0.5126
# Navy AD * # Night Flight	0.5097
# Dest Diff APOD * # Stops	0.5089
Tot AF * # ULNs > 20	0.5085
Sched Pax * # ULNs > 1	0.5081
# Reverse Travel * # Night Flight	0.5081
# Army AD * Tot Navy	0.5067
# AF AD * # ULNs > 5	0.5063
# Army AD * # Navy AD	0.5057
Tot Navy * # Night Flight	0.5057
Tot AF * Length Flight	0.5027
# GR * # Navy AD	0.5025
Tot Army * # ULNs > 1	0.5006
# GR * Tot Navy	0.4999
# Navy AD * Sched Pax	0.4992
# ULNs > 1	0.4991
Tot Navy * Sched Pax	0.4966
# Navy AD * Tot ULNs	0.4959
# ULNs > 1 * # Stops	0.4956
# AF AD * Tot AF	0.4938
Tot Navy * Tot ULNs	0.4937
# AF AD * # ULNs > 10	0.4916
Tot ULNs * # Dest Diff APOD	0.4887
# Single ULNs * # ULNs > 5	0.4885
Tot Army * # Agg Mil	0.487
# ULNs > 1^2	0.4857
Sched Pax * Tot ULNs	0.4847
Tot ULNs * # Night Flight	0.4843

# ULNs > 5 * # Night Flight	0.4834
Tot Army * # AF AD	0.483
# ULNs > 5 * # Reverse Travel	0.4812
# GR * # Agg Mil	0.4793
# ULNs > 10 * Tot ULNs	0.4787
Tot AF * # Night Flight	0.4778
# ULNs > 5 * Length Flight	0.4776
Tot Army * # ULNs > 5	0.4741
Tot ULNs * Length Flight	0.4732
# AF AD^2	0.4726
# Army AD * # Reverse Travel	0.4708
Tot ULNs	0.4704
Tot AF * Tot ULNs	0.47
# ULNs > 10 * # Reverse Travel	0.4685
Tot AF * # Ded Mil	0.4681
Tot AF * # Agg Mil	0.4677
# Navy AD * # Stops	0.4653
Tot Navy * # Stops	0.465
# AF GR * # ULNs > 5	0.4634
# Navy AD	0.4624
Tot Navy	0.4603
# ULNs > 20 * # Reverse Travel	0.4596
# Marine AD * # Agg Mil	0.4587
# AF AD * Tot ULNs	0.4571
# AF AD * # ULNs > 20	0.457
# AF AD * Length Flight	0.4561
# GR * ULNs > 1	0.456
# Army AD * # ULNs > 1	0.4541
# Single ULNs * # ULNs > 1	0.4535
# AF AD * # Agg Mil	0.453
Tot ULNs * # Stops	0.453
# Navy AD * # Single ULNs	0.45
Tot AF * # ULNs > 50	0.449
# Navy AD * Length	0.4482
Tot Navy * Length Flight	0.4478
Tot Navy * # Single ULNs	0.4477
# Single ULNs * # Reverse Travel	0.4433
# AD * # Army GR	0.443
# AF AD * # Night Flight	0.4407
# Navy AD * # ULNs > 10	0.4407
# ULNs > 5 * # Dest Diff APOD	0.4392
# ULNs > 5 * # Stops	0.4383
# Dest Diff APOD * Length Flight	0.4378
Tot Navy * # ULNs > 10	0.4365
# Army GR * Tot AF	0.4363
# AF GR * # ULNs > 10	0.4343

# GR * Sched Pax	0.4327
# Ded Mil * # Agg Mil	0.4303
# AF AD * # Ded Mil	0.4295
# GR * # AF GR	0.4293
Tot Army * # Reverse Travel	0.4262
# GR * # Night Flight	0.4256
# AD * # Navy AD	0.425
# GR * # ULNs > 5	0.4249
# Single ULNs * # Agg Mil	0.4245
# AD * Tot Navy	0.4222
# AF AD * # ULNs > 50	0.4221
Tot AF * # Stops	0.422
# Army GR * # AF AD	0.4209
Sched Pax * Length Flight	0.4198
Tot Army * # ULNs > 10	0.4187
# AF GR * # ULNs > 1	0.4159
# Army GR * # Navy AD	0.414
Tot AF * # Single ULNs	0.4138
# AF AD * # Navy AD	0.4137
# GR * Tot ULNs	0.4136
# AF AD * Tot Navy	0.4134
# Army GR * # Agg Mil	0.412
Tot AF * Tot Navy	0.4107
Tot AF * # Navy AD	0.4106
# Army GR * Tot Navy	0.4103
# GR * # Dest Diff APOD	0.4098
Tot Army * Tot ULNs	0.408
# Reverse Travel * # Ded Mil	0.4075
# GR * # ULNs > 10	0.4067
# Reverse Travel^2	0.4065
# AD * Tot ULNs	0.4058
# Single ULNs * Length Flight	0.4048
# Marine GR * Tot Navy	0.4039
# Marine GR * # Navy AD	0.4032
Sched Pax * # Single ULNs	0.4003
# Single ULNs * # Stops	0.4002
# AF GR * # Reverse Travel	0.4001
Sched Pax * # Stops	0.3995
# ULNs > 1 * # ULNs > 5	0.3983
#GR	0.397
Tot AF * Weekend Flight	0.3966
# AF AD * # Single ULNs	0.3965
# GR * # Army AD	0.3952
# Single ULNs * # ULN > 10	0.3942
# AF GR	0.3927
# AF GR * Sched Pax	0.3926

# AF GR * # Agg Mil	0.3922
# Marine GR * # Agg Mil	0.3906
# Single ULNs	0.3903
# AF AD * Weekend Flight	0.3894
# Single ULNs * # Night Flight	0.3885
# Army AD * # ULNs > 5	0.3875
Tot Army * # Dest Diff APOD	0.3873
# Navy AD * # ULNs > 20	0.3863
# AF GR * # Dest Diff APOD	0.3862
# GR * # Stops	0.3851
Tot ULNs^2	0.385
# Army AD * Tot AF	0.3838
Tot Army * Sched Pax	0.3838
# AF GR * # Stops	0.3838
# GR * Length Flight	0.3836
Tot Navy * # ULNs > 20	0.3835
# ULNs > 50 * # Reverse Travel	0.3821
# Stops * # Night Flight	0.3805
# AF GR * # ULNs > 20	0.3798
# Single ULNs * # Dest Diff APOD	0.378
# Navy AD^2	0.3772
# GR * # ULNs > 20	0.3766
# Navy AD * Tot Navy	0.3761
Tot Navy^2	0.375
# ULNs > 20 * Tot ULNs	0.3741
# AF AD * # Stops	0.3737
# Army GR * # ULNs > 1	0.3732
# AF GR * Length Flight	0.3699
# AD * # Single ULNs	0.3663
# Army GR * # ULNs > 5	0.3635
# Army AD * # AF AD	0.3622
# Army AD * # Agg Mil	0.3607
# Marine GR * # ULNs > 1	0.3601
# Army GR * # Night Flight	0.3554
# GR * # Reverse Travel	0.354
# Army GR * # ULNs > 10	0.3506
# Army GR * # Marine GR	0.3505
# GR * # Marine GR	0.3491
# AD * # AF GR	0.349
Length of Flight	0.3465
# Army AD * # Army GR	0.3458
# Marine GR * # Reverse Travel	0.3454
# AF GR * Tot ULNs	0.3441
# Army GR * Sched Pax	0.3439
# Army GR * # Dest Diff APOD	0.343
# Army AD * Tot ULNs	0.3421

# AF GR * # Night flight	0.3412
# ULNs > 1 * # ULNs > 10	0.3395
Tot Army * # ULNs > 20	0.3387
# Stops	0.3386
Tot Army * # AF GR	0.3382
# AF GR * Tot Marine	0.3362
# Navy AD * Weekend Flight	0.336
# Agg Mil * Weekend Flight	0.3346
# Army GR * # AF GR	0.3345
Sched Pax * # Dest Diff APOD	0.3339
# AF AD * # AF GR	0.3338
# AF GR * Tot AF	0.3337
# ULNs > 50 * # Agg Mil	0.3334
Tot Army	0.3333
Length Flight * # Night Flight	0.3327
Tot Navy * Weekend Flight	0.3324
Sched Pax * # ULNs > 5	0.3323
# Single ULNs * # ULNs > 20	0.3322
Tot Army * # Marine GR	0.3291
# Marine GR * Tot ULNs	0.3289
# AF GR * Tot Navy	0.326
# AF GR * # Navy AD	0.3254
# GR * # Single ULNs	0.3244
Tot Army * # Night Flight	0.3235
# GR * Tot Army	0.3232
# Stops * Length Flight	0.3213
# AF GR * # Single ULNs	0.3204
# AD * # ULNs > 1	0.3198
Tot Army * # Stops	0.3198
# Marine GR * # Stops	0.3176
# ULNs > 10 * # Night Flight	0.317
# Marine GR * # ULNs > 5	0.3164
# ULNs > 10 * Length Flight	0.316
Length Flight^2	0.3157
Tot Army * # Single ULNs	0.3153
# Single ULNs^2	0.3142
# Dest Diff APOD	0.3137
Tot Army * Length Flight	0.312
# AF GR * # ULNs > 50	0.3106
# Army GR	0.3089
# Army GR * # ULNs > 20	0.3072
# Navy AD * # ULNs > 50	0.3052
Tot Navy * # ULNs > 50	0.3045
Sched Pax * # Night Flight	0.304
# Dest Diff APOD * # Night Flight	0.3011
# AF GR * # Marine AD	0.3007

# AF GR^2	0.3
# GR * # Ded Mil	0.2995
# Army GR * Length Flight	0.2967
# ULNs > 1 * Weekend Flight	0.2963
# Army GR * # Reverse Travel	0.296
# Army GR * Tot ULNs	0.2939
# Army GR * # Stops	0.2926
# ULNs > 5	0.2925
# AF GR * # Ded Mil	0.2913
# Army AD * # Single ULNs	0.2886
# ULNs > 50 * Tot ULNs	0.2883
# Stops^2	0.2867
# Dest Diff APOD^2	0.2852
# ULNs > 10 * # Stops	0.2832
# GR^2	0.2802
# Marine GR * # ULNs > 10	0.2796
# Marine GR * Sched Pax	0.2773
# Army GR * Tot Army	0.2743
# Army AD * # ULNs > 10	0.2739
# Marine GR^2	0.2706
# AD * Tot Army	0.2687
# ULNs > 1 * # ULNs > 20	0.2682
# Reverse Travel * Weekend Flight	0.2668
# Marine GR * Length Flight	0.2657
# ULNs > 10 * # Dest Diff APOD	0.2652
Tot Marine * # Reverse Travel	0.2616
# Army AD * # Marine GR	0.2609
# Single ULNs * # ULNs > 50	0.2589
# Night Flight	0.2585
# AD * # Stops	0.2581
Sched Pax	0.258
Tot Army^2	0.2567
# Single ULNs * # Ded Mil	0.2549
# Marine GR * # Single ULNs	0.2545
ULNs > 5^2	0.2542
# Marine GR	0.2529
# Marine GR * # Dest Diff APOD	0.2524
# ULNs > 5 * Weekend Flight	0.2477
Tot AF * # Marine GR	0.2446
Sched Pax^2	0.2437
# Night Flight^2	0.2417
# Army GR * # Ded Mil	0.2415
# GR * # Army GR	0.2373
# Marine GR * # Night Flight	0.237
# AF AD * # Marine GR	0.2352
# AD * Length Flight	0.2339

# GR * Weekend Flight	0.2326
# Army AD * # Dest Diff APOD	0.2305
# Army AD * # AF GR	0.2288
# ULNs > 20 * # Night Flight	0.2243
Tot AF * # Joint AD	0.2217
Tot AF * Tot Joint	0.2214
# AF GR * # Marine GR	0.221
# Marine GR * # ULNs > 20	0.2201
# GR * # ULNs > 50	0.22
# GR * Tot Marine	0.2193
# AF AD * # Joint AD	0.2176
# AF AD * Tot Joint	0.2175
# Army AD * Sched Pax	0.2172
# Navy AD * # Ded Mil	0.2137
# Army GR^2	0.2129
# Army GR * # Single ULNs	0.2124
Tot Navy * # Ded Mil	0.2104
# Marine AD * # Reverse Travel	0.2102
# Army GR * Weekend Flight	0.2097
Tot Army * Tot Marine	0.2066
# Stops * Weekend Flight	0.205
# ULNs > 1 * # ULNs > 50	0.2035
# Army AD * # ULNs > 20	0.2021
# Joint AD * # Marine GR	0.1994
Tot Joint * # Marine GR	0.1994
# Army AD * # Stops	0.1979
# ULNs > 20 * # Dest Diff APOD	0.1952
# AD * # Marine GR	0.1917
# ULNs > 20 * Length Flight	0.1894
# Joint AD * # IAP	0.1889
Tot Joint * # IAP	0.1889
# Joint AD * # Single ULNs	0.1813
# Joint AD * Tot ULNs	0.1798
Tot Joint * # Single ULNs	0.1795
# Army AD * # Night Flight	0.1774
# Army GR * # ULNs > 50	0.1772
Tot Joint * Tot ULNs	0.1772
# Army AD	0.1748
# Joint AD * # Agg Mil	0.1729
# Army AD * Length Flight	0.1722
Tot Army * Weekend Flight	0.1717
# ULNs > 5 * # ULNs > 10	0.1707
# Marine GR * Weekend Flight	0.1689
# Joint AD * # Dest Diff APOD	0.1688
Tot Joint * # Agg Mil	0.1684
# Army GR * Tot Marine	0.1672

# ULNs > 20 * # Stops	0.1672
Tot Joint * # Dest Diff APOD	0.1646
# ULNs > 10 * Weekend Flight	0.1629
# GR * # Joint AD	0.1611
# Army AD * # IAP	0.1596
# Joint AD * # Reverse Travel	0.1587
# Army AD * # Joint AD	0.158
# Night Flight * Weekend Flight	0.1574
# AF AD * # IAP	0.1572
Tot AF * # IAP	0.1572
Tot Army * # Joint AD	0.1562
# GR * Tot Joint	0.156
# Army AD * Tot Joint	0.1549
# ULNs > 20 * # IAP	0.1539
Length Flight * Weekend Flight	0.1539
Tot Joint * # Reverse Travel	0.1533
Tot Army * Tot Joint	0.1522
# Joint AD * # Stops	0.1503
# AD * # Night Flight	0.15
# Joint AD * Sched Pax	0.1491
# AD * # Army AD	0.1481
# Dest Diff APOD * Weekend Flight	0.147
Tot Joint * # Stops	0.1466
# AD * # Joint AD	0.1457
Tot AF * Tot Marine	0.1448
Tot Joint * Sched Pax	0.1443
# Army AD * Tot Marine	0.1439
Sched Pax * Weekend Flight	0.1439
Tot ULNs * Weekend Flight	0.1433
# AD * # IAP	0.1431
# AF GR * Weekend Flight	0.1417
# Army GR * # Joint AD	0.1413
# AF GR * # Joint AD	0.1412
# AD * Tot Joint	0.1409
# AF GR * Tot Joint	0.1405
# ULNs > 20 * Weekend Flight	0.1391
# Joint AD	0.1375
# Joint AD * Length Flight	0.1363
# Army GR * Tot Joint	0.1362
Tot Joint	0.1326
Tot Joint * Length Flight	0.1317
# Joint AD * # ULNs > 50	0.1184
# ULNs > 10 * # IAP	0.118
# AD * # Dest Diff APOD	0.1178
Tot Army * # Marine AD	0.1167
# AF GR * # IAP	0.1157

# Joint AD * # Ded Mil	0.1156
# Army AD * Tot Army	0.1155
Sched Pax * # IAP	0.1151
# Dest Diff APOD * # IAP	0.1151
Tot Joint * # ULNs > 50	0.1142
Tot AF * # Marine AD	0.1128
# Joint AD * Tot Navy	0.1127
# Joint AD * # Navy AD	0.1123
Tot Army * # IAP	0.1117
Tot Joint * # Ded Mil	0.1116
# ULNs > 50 * Weekend Flight	0.1114
# IAP * Weekend Flight	0.1099
# Joint AD * # ULNs > 10	0.1091
Tot Joint * Tot Navy	0.1087
# IAP * # Stops	0.1086
Tot Army * # Ded Mil	0.1085
Tot Joint * # Navy AD	0.1083
Tot Army * # ULNs > 50	0.1078
# ULNs > 50 * # IAP	0.1076
# Joint AD * # ULNs > 5	0.1069
# GR * # Marine AD	0.1065
# IAP * Length Flight	0.1061
Sched Pax * # ULNs > 10	0.1049
Tot Joint * # ULNs > 10	0.1046
# Army AD * Weekend Flight	0.1045
# Marine GR * # ULNs > 50	0.104
# Joint AD * # ULNs > 1	0.1029
Tot Joint * # ULNs > 5	0.102
# IAP	0.1012
Tot Marine * # Navy AD	0.1009
# ULNs > 5 * # IAP	0.0993
# IAP * # Night Flight	0.0992
Tot Joint * # ULNs > 1	0.0983
# IAP * # Ded Mil	0.0981
# Navy AD * # IAP	0.0975
# IAP^2	0.097
Tot Marine * Tot Navy	0.0965
Tot Navy * # IAP	0.0944
# Reverse Travel * # IAP	0.0938
# Joint AD * # ULNs > 20	0.0914
# Army AD * # Marine AD	0.0902
Tot Joint * # ULNs > 20	0.0875
# AD * Weekend Flight	0.0849
# ULNs > 1 * # IAP	0.0843
# Joint AD^2	0.0843
# AF AD * Tot Marine	0.0839

# GR * # IAP	0.0811
# Joint AD * Tot Joint	0.0807
# Army GR * # IAP	0.0796
# Army GR * # Marine AD	0.0776
Tot Joint^2	0.0772
# Single ULNs * Weekend Flight	0.0758
Tot ULNs * # IAP	0.0753
# IAP * # Agg Mil	0.0753
# ULNs > 5 * # ULNs > 20	0.0727
# Single ULNs * # IAP	0.0639
# Marine AD * # Navy AD	0.0625
Tot Marine * # Single ULNs	0.0606
# AD * # ULNs > 5	0.0605
# ULNs > 50 * # Dest Diff APOD	0.0603
# AF AD * # Marine AD	0.0594
# Joint AD * # Night Flight	0.0591
# ULNs > 50 * # Stops	0.0587
# Marine AD * Tot Navy	0.0586
# Joint AD * Tot Marine	0.0583
Tot Joint * # Night Flight	0.0578
Tot Joint * Tot Marine	0.0568
# Ded Mil * # Stops	0.0568
# ULNs > 5 * # ULNs > 50	0.0534
# Army AD * # Ded Mil	0.0529
# Army AD^2	0.0501
# ULNs > 10	0.04
# Joint AD * Weekend Flight	0.0378
Tot Joint * Weekend Flight	0.0378
# AF GR * # ULNs > 100	0.036
# Army AD * # ULNs > 50	0.0304
# AF GR * # ULNs > 200	0.026
# Joint AD * # Navy GR	0.026
Tot Joint * # Navy GR	0.026
# Navy GR * # ULNs > 200	0.026
# ULNs > 100 * # IAP	0.0256
# Marine AD * # Single ULNs	0.0241
# AF GR * # Navy GR	0.0187
# Joint GR	0.018
# AD * # Joint GR	0.018
# GR * # Joint GR	0.018
# Army AD * # Joint GR	0.018
# Army GR * # Joint GR	0.018
Tot Army * # Joint GR	0.018
# AF AD * # Joint GR	0.018
# AF GR * # Joint GR	0.018
Tot AF * # Joint GR	0.018

# Joint AD * # Joint GR	0.018
# Joint GR * Tot Joint	0.018
# Joint GR * # Marine AD	0.018
# Joint GR * # Marine GR	0.018
# Joint GR * Tot Marine	0.018
# Joint GR * # Navy AD	0.018
# Joint GR * Tot Navy	0.018
# Joint GR * Sched Pax	0.018
# Joint GR * # Single ULNs	0.018
# Joint GR * # ULNs > 1	0.018
# Joint GR * # ULNs > 5	0.018
# Joint GR * # ULNs > 10	0.018
# Joint GR * # ULNs > 20	0.018
# Joint GR * # ULNs > 50	0.018
# Joint GR * Tot ULNs	0.018
# Joint GR * # Dest Diff APOD	0.018
# Joint GR * # Reverse Travel	0.018
# Joint GR * # Ded Mil	0.018
# Joint GR * # Agg Mil	0.018
# Joint GR * # Stops	0.018
# Joint GR * Length Flight	0.018
# Joint GR * # Night Flight	0.018
# Joint GR^2	0.018
# Marine GR * # Navy GR	0.0162
ULNs > 10^2	0.0145
Tot AF * # ULNs > 100	0.0131
# Joint AD * # ULNs > 200	0.011
Tot Joint * # ULNs > 200	0.011
# Army AD * # Navy GR	0.0066
Tot Joint * # Marine AD	0.0059
# Army GR * # ULNs > 200	0.0052
# ULNs > 200 * # Agg Mil	0.0052
# Joint AD * # Marine AD	0.0051
# ULNs > 50 * Length Flight	0.0039
# Joint GR * # Navy GR	0
# Joint GR * # ULNs > 100	0
# Joint GR * # ULNs > 200	0
# Joint GR * # IAP	0
# Joint GR * Weekend Flight	0
# ULNs > 200 * # IAP	0
# GR * # ULNs > 200	-0.0047
# Navy GR * # Agg Mil	-0.0069
# ULNs > 50 * # Night Flight	-0.0092
# ULNs > 100 * # Agg Mil	-0.0107
# Army GR * # ULNs > 100	-0.0117
Tot AF * # Navy GR	-0.0131

# Ded Mil * Weekend Flight	-0.0138
Tot Navy * # ULNs > 200	-0.015
Tot Army * # Navy GR	-0.0155
# AF AD * # ULNs > 100	-0.0163
Sched Pax * # ULNs > 20	-0.0188
# Navy GR * # Stops	-0.024
# Navy GR * Weekend Flight	-0.024
# Ded Mil * Length Flight	-0.0248
Tot AF * # ULNs > 200	-0.0253
# Navy GR * Length Flight	-0.0253
# Joint AD * # ULNs > 100	-0.0256
Tot Joint * # ULNs > 100	-0.0256
# Navy GR * # ULNs > 50	-0.0308
# Navy GR * # ULNs > 100	-0.0308
# GR * # Navy GR	-0.0313
# Marine GR * Tot Marine	-0.0316
# Navy GR * # Single ULNs	-0.0351
# GR * ULNs > 100	-0.0356
# AD * Sched Pax	-0.0373
# Navy GR * Tot ULNs	-0.0378
# Navy AD * # ULNs > 200	-0.0381
# Single ULNs * ULNs > 200	-0.0383
# Army GR * # Navy GR	-0.0405
# AF AD * # Navy GR	-0.0425
* ULNs > 1 * # Ded Mil	-0.0433
# Marine AD * # IAP	-0.0434
# Navy GR * # IAP	-0.0435
# Navy GR * # Reverse Travel	-0.0439
Tot Marine * # IAP	-0.044
# ULNs > 200 * Tot ULNs	-0.0458
# Navy GR^2	-0.0461
# Navy GR * # Night Flight	-0.0479
# Marine GR * # Ded Mil	-0.0483
# Navy GR * # Dest Diff APOD	-0.0491
# Navy GR * # ULNs > 1	-0.0512
Tot Marine * Tot ULNs	-0.053
# Navy GR * Sched Pax	-0.053
# Navy GR	-0.0538
Tot Army * # ULNs > 100	-0.0546
# Army AD * # ULNs > 100	-0.0557
# Ded Mil * # Night Flight	-0.0575
# AD * # Navy GR	-0.0598
Tot Army * # ULNs > 200	-0.0598
# Marine GR * # IAP	-0.0618
# Navy GR * # Ded Mil	-0.062
# Army AD * # ULNs > 200	-0.0623

# Marine GR * # ULNs > 200	-0.0659
# Navy GR * # ULNs > 20	-0.0678
# Navy GR * # ULNs > 5	-0.0719
# ULNs > 20	-0.0724
# ULNs > 10 * # ULNs > 20	-0.0752
# ULNs > 200 * # Night Flight	-0.0833
# ULNs > 200 * Weekend Flight	-0.0846
# Navy GR * # ULNs > 10	-0.0859
# Single ULNs * # ULNs > 100	-0.0862
# ULNs > 100 * # Reverse Travel	-0.0909
# ULNs > 1 * # ULNs > 200	-0.0918
Sched Pax * # ULNs > 50	-0.0942
# ULNs > 200 * # Dest Diff APOD	-0.0942
# ULNs > 200 * # Stops	-0.0977
# Navy GR * Tot Navy	-0.0981
# ULNs > 10 * # ULNs > 50	-0.0982
Tot Marine * # Navy GR	-0.101
# ULNs > 5 * # ULNs > 200	-0.1015
# Navy AD * # Navy GR	-0.1029
# Marine AD * # Navy GR	-0.1034
# AF AD * # ULNs > 200	-0.1041
ULNs > 50^2	-0.1046
# ULNs > 200 * Length Flight	-0.1052
# Marine AD * Tot ULNs	-0.106
# Marine AD * # Marine GR	-0.1099
# ULNs > 10 * # ULNs > 200	-0.1164
Tot ULNs * # Ded Mil	-0.1168
# Dest Diff APOD * # Ded Mil	-0.1168
Tot Marine * # ULNs > 200	-0.1172
# Marine AD * # ULNs > 200	-0.1174
# ULNs > 20 * # ULNs > 200	-0.1183
ULNs > 20^2	-0.1203
Sched Pax * # ULNs > 200	-0.1232
# ULNs > 200 * # Reverse Travel	-0.1234
#AD	-0.1238
# ULNs > 50	-0.1284
Tot Marine * Weekend Flight	-0.1293
# AD * # ULNs > 200	-0.132
# AD * # ULNs > 10	-0.1331
Tot Marine * # Night Flight	-0.1337
# ULNs > 200 * # Ded Mil	-0.1352
# ULNs > 20 * # ULNs > 50	-0.1382
# Marine GR * # ULNs > 100	-0.1383
# ULNs > 200	-0.1395
# ULNs > 100 * # ULNs > 200	-0.1395
# ULNs > 200^2	-0.1395

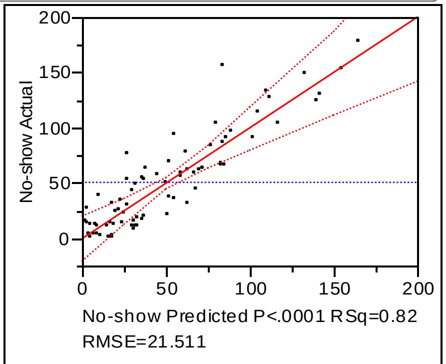
Tot Marine * # Stops	-0.1406
# Marine AD * Weekend Flight	-0.1431
# ULNs > 50 * # ULNs > 200	-0.1439
# Marine AD * # Night Flight	-0.1569
# AD * # ULNs > 50	-0.1581
AD^2	-0.1637
# ULNs > 100 * Tot ULNs	-0.1646
# Marine AD * # Stops	-0.175
# AD * # ULNs > 20	-0.1792
# ULNs > 100 * # Stops	-0.1844
# ULNs > 100 * Weekend Flight	-0.1847
Tot Navy * # ULNs > 100	-0.2026
# Navy AD * # ULNs > 100	-0.2041
# ULNs > 5 * # Ded Mil	-0.2175
# ULNs > 50 * # Ded Mil	-0.2341
# ULNs > 100 * # Night Flight	-0.2446
# ULNs > 100 * Length Flight	-0.2719
Tot Marine * # ULNs > 1	-0.2773
Sched Pax * # Ded Mil	-0.2808
Tot Marine * Length Flight	-0.283
# ULNs > 100 * # Dest Diff APOD	-0.2897
Tot Marine * # Dest Diff APOD	-0.3029
# ULNs > 10 * # Ded Mil	-0.3142
# ULNs > 20 * # Ded Mil	-0.3143
# Marine AD * Length	-0.3185
# Marine AD * # ULNs > 1	-0.3252
# AD * # Ded Mil	-0.3253
# Marine AD * # Dest Diff APOD	-0.3266
# ULNs > 1 * # ULNs > 100	-0.3276
# ULNs > 100^2	-0.3411
# ULNs > 50 * # ULNs > 100	-0.3516
# Ded Mil	-0.3686
Tot Marine * # ULNs > 50	-0.3778
# Ded Mil^2	-0.3781
# Marine AD * # ULN > 50	-0.3832
# ULNs > 5 * # ULNs > 100	-0.3841
Sched Pax * # ULNs > 100	-0.3882
Tot Marine * # ULNs > 5	-0.3888
# AD * # ULNs > 100	-0.3982
# ULNs > 100	-0.4043
# ULNs > 20 * # ULNs > 100	-0.4093
# ULNs > 100 * # Ded Mil	-0.4173
# Marine AD * # ULN > 5	-0.4188
# ULNs > 10 * # ULNs > 100	-0.42
Tot Marine * # ULNs > 100	-0.4224
# Marine AD * # ULNs > 100	-0.4234

Tot Marine * # ULNs > 20	-0.4366
Tot Marine * Sched Pax	-0.4381
# Marine AD * # ULN > 20	-0.4476
Tot Marine * # ULNs > 10	-0.4548
# AD * Tot Marine	-0.4569
# Marine AD * Sched Pax	-0.4571
# AD * # Marine AD	-0.4668
# Marine AD * # ULN > 10	-0.47
Tot Marine * # Ded Mil	-0.4896
# Marine AD * # Ded Mil	-0.4915
Tot Marine^2	-0.4925
# Marine AD * Tot Marine	-0.496
# Marine AD^2	-0.4974
Tot Marine	-0.5066
# Marine AD	-0.5242

Appendix E: Model Analysis

Response No-show

Actual by Predicted Plot



Summary of Fit

RSquare	0.824243
RSquare Adj	0.755894
Root Mean Square Error	21.51075
Mean of Response	51.27632
Observations (or Sum Wgts)	76

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	21	117178.74	5579.94	12.0592
Error	54	24986.46	462.71	Prob > F
C. Total	75	142165.20		<.0001

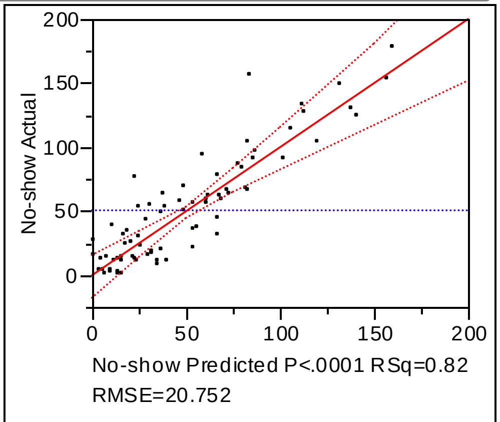
Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t
Intercept	-1.721992	12.71557	-0.14	0.8928
#GR	0.0529232	0.066688	0.79	0.4309
# AF GR	-0.489738	0.285721	-1.71	0.0923
Tot AF	0.3754023	0.068355	5.49	<.0001
# Marine AD	-0.06512	0.032881	-1.98	0.0528
# Navy AD	0.5562907	0.167097	3.33	0.0016
Sched Pax	0.1432394	0.064975	2.20	0.0318
# Single ULNs	7.8778473	6.580089	1.20	0.2364
# ULNs > 1	7.0058322	6.46797	1.08	0.2836
# ULNs > 5	0.4578746	1.218361	0.38	0.7085
# ULNs > 100	-9.850495	7.253572	-1.36	0.1801
Tot ULNs	-7.954701	6.576109	-1.21	0.2317
# Dest Diff APOD	0.0219428	0.035354	0.62	0.5374
# Reverse Travel	0.324836	0.162806	2.00	0.0511
# Agg Mil	0.0339081	0.048646	0.70	0.4888
Weekend Flight[0]	-6.753019	2.929786	-2.30	0.0250
(Tot AF-40.0658)*(# Reverse Travel-20.8947)	-0.000339	0.00225	-0.15	0.8810
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0.0018723	0.000933	2.01	0.0499
(# Dest Diff APOD-229.355)*(# Agg Mil-75.1053)	-0.000038	0.000381	-0.10	0.9199
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0.0118461	0.006281	1.89	0.0647
(Tot AF-40.0658)*(Sched Pax-316.118)	-0.002148	0.00123	-1.75	0.0866
(# ULNs > 5-9.43421)*(# Agg Mil-75.1053)	-0.001469	0.006304	-0.23	0.8166

Figure 16. Full Model

Response No-show

Actual by Predicted Plot



Summary of Fit

RSquare	0.818246
RSquare Adj	0.772807
Root Mean Square Error	20.75216
Mean of Response	51.27632
Observations (or Sum Wgts)	76

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	15	116326.08	7755.07	18.0077
Error	60	25839.12	430.65	Prob > F
C. Total	75	142165.20		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-2.162024	11.50056	-0.19	0.8515
# AF GR	-0.480917	0.240352	-2.00	0.0499
Tot AF	0.3507924	0.055256	6.35	<.0001
# Marine AD	-0.079962	0.02726	-2.93	0.0047
# Navy AD	0.5093058	0.140692	3.62	0.0006
Sched Pax	0.1840375	0.047197	3.90	0.0002
# Single ULNs	8.6300104	5.811246	1.49	0.1428
# ULNs > 1	7.9478057	5.761767	1.38	0.1729
# ULNs > 100	-11.70837	6.427883	-1.82	0.0735
Tot ULNs	-8.712557	5.807759	-1.50	0.1388
# Reverse Travel	0.4006549	0.119711	3.35	0.0014
# Agg Mil	0.0252835	0.045162	0.56	0.5777
Weekend Flight[0]	-7.15948	2.698181	-2.65	0.0102
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0.0019138	0.00051	3.75	0.0004
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0.0100194	0.005386	1.86	0.0678
(Tot AF-40.0658)*(Sched Pax-316.118)	-0.002169	0.001044	-2.08	0.0420

Figure 17. 1st Reduced Model

Custom Test

1st Reduced Model from Full Model

Parameter		
Intercept	0	0
#GR	0	1
# AF GR	0	0
Tot AF	0	0
# Marine AD	0	0
# Navy AD	0	0
Sched Pax	0	0
# Single ULNs	0	0
# ULNs > 1	0	0
# ULNs > 5	0	1
# ULNs > 100	0	0
Tot ULNs	0	0
# Dest Diff APOD	0	1
# Reverse Travel	0	0
# Agg Mil	0	0
Weekend Flight[0]	0	0
(Tot AF-40.0658)*(# Reverse Travel-20.8947)	0	1
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0	0
(# Dest Diff APOD-229.355)*(# Agg Mil-75.1053)	0	1
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0	0
(Tot AF-40.0658)*(Sched Pax-316.118)	0	0
(# ULNs > 5-9.43421)*(# Agg Mil-75.1053)	0	0
=	0	1

Value	0	-0.467636478
Std Error	0	1.2204541152
t Ratio	0	-0.383165965
Prob>|t|	1	0.7031010029
SS	0	67.933630695

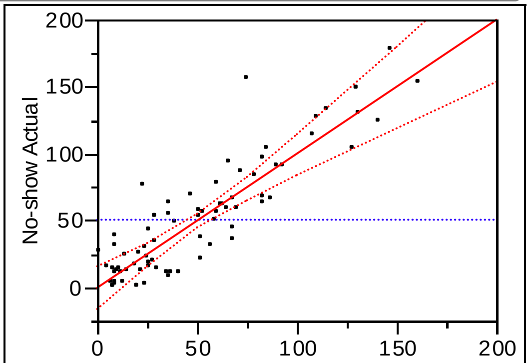
Sum of Squares	67.933630695
Numerator DF	1
F Ratio	0.1468161565
Prob > F	0.7031010029

WARNING: Non-Testable Contrast

Figure 18. F-test Comparison: Full Model to 1st Model

Response No-show

Actual by Predicted Plot



Summary of Fit

RSquare	0.799267
RSquare Adj	0.761032
Root Mean Square Error	21.28315
Mean of Response	51.27632
Observations (or Sum Wgts)	76

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	12	113627.92	9468.99	20.9041
Error	63	28537.27	452.97	Prob > F
C. Total	75	142165.20		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t
Intercept	-3.801288	11.77228	-0.32	0.7478
# AF GR	-0.535066	0.23987	-2.23	0.0293
Tot AF	0.3067859	0.053159	5.77	<.0001
# Marine AD	-0.082752	0.026857	-3.08	0.0031
# Navy AD	0.3839731	0.132407	2.90	0.0051
Sched Pax	0.1359788	0.042889	3.17	0.0024
# ULNs > 100	-3.468345	5.477746	-0.63	0.5289
# Reverse Travel	0.405054	0.12055	3.36	0.0013
# Agg Mil	-0.002123	0.043606	-0.05	0.9613
Weekend Flight[0]	-8.020831	2.733148	-2.93	0.0047
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0.0017186	0.000505	3.40	0.0012
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0.0138408	0.005268	2.63	0.0108
(Tot AF-40.0658)*(Sched Pax-316.118)	-0.002063	0.001057	-1.95	0.0555

Figure 19. 2nd Reduced Model

Custom Test

Second to third model

Parameter		
Intercept	0	0
# AF GR	0	0
Tot AF	0	0
# Marine AD	0	0
# Navy AD	0	0
Sched Pax	0	0
# Single ULNs	0	1
# ULNs > 1	0	1
# ULNs > 100	0	0
Tot ULNs	0	1
# Reverse Travel	0	0
# Agg Mil	0	0
Weekend Flight[0]	0	0
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0	0
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0	0
(Tot AF-40.0658)*(Sched Pax-316.118)	0	0
=	0	0

Value	0	7.8652594136
Std Error	0	5.7668853592
t Ratio	0	1.3638660947
Prob>|t|	1	0.1777046301
SS	0	801.06901718

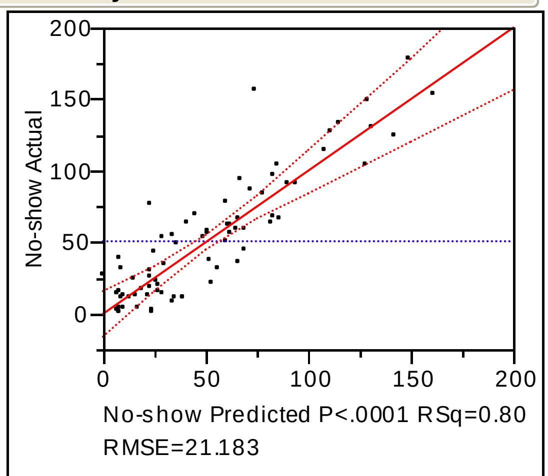
Sum of Squares	801.06901718
Numerator DF	1
F Ratio	1.8601307244
Prob > F	0.1777046301

WARNING: Non-Testable Contrast

Figure 20. F-Test Comparison: 1st Model to 2nd Model

Response No-show

Actual by Predicted Plot



Summary of Fit

RSquare	0.797989
RSquare Adj	0.763269
Root Mean Square Error	21.1833
Mean of Response	51.27632
Observations (or Sum Wgts)	76

Analysis of Variance

Source	DF	Sum of Square:	Mean Square	F Ratio
Model	11	113446.32	10313.3	22.9832
Error	64	28718.87	448.7	Prob > F
C. Total	75	142165.20		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t
Intercept	-3.587261	11.71222	-0.31	0.7604
# AF GR	-0.557183	0.236199	-2.36	0.0214
Tot AF	0.3186467	0.049515	6.44	<.0001
# Marine AD	-0.083432	0.026709	-3.12	0.0027
# Navy AD	0.4001781	0.129301	3.09	0.0029
Sched Pax	0.1275542	0.040581	3.14	0.0025
# Reverse Travel	0.4222914	0.116885	3.61	0.0006
# Agg Mil	-0.000246	0.043301	-0.01	0.9955
Weekend Flight[0]	-8.058307	2.719688	-2.96	0.0043
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0.0017431	0.000501	3.48	0.0009
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0.0137576	0.005242	2.62	0.0108
(Tot AF-40.0658)*(Sched Pax-316.118)	-0.001991	0.001046	-1.90	0.0615

Figure 21. 3rd Reduced Model

Custom Test

Parameter		
Intercept	0	0
# AF GR	0	0
Tot AF	0	0
# Marine AD	0	0
# Navy AD	0	0
Sched Pax	0	0
# ULNs > 100	0	1
# Reverse Travel	0	0
# Agg Mil	0	0
Weekend Flight[0]	0	0
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0	0
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0	0
(Tot AF-40.0658)*(Sched Pax-316.118)	0	0
=	0	0

Value	0	-3.468344718
Std Error	0	5.4777462749
t Ratio	0	-0.63317002
Prob>|t|	1	0.5289144511
SS	0	181.59865536

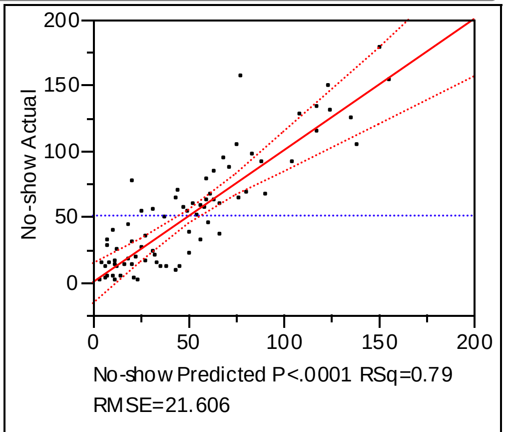
Sum of Squares	181.59865536
Numerator DF	1
F Ratio	0.4009042741
Prob > F	0.5289144511

WARNING: Non-Testable Contrast

Figure 22. F-Test Comparison: 2nd Model to 3rd Model

Response No-show

Actual by Predicted Plot



Summary of Fit

RSquare	0.786558
RSquare Adj	0.75372
Root Mean Square Error	21.60629
Mean of Response	51.27632
Observations (or Sum Wgts)	76

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	10	111821.14	11182.1	23.9532
Error	65	30344.06	466.8	Prob > F
C. Total	75	142165.20		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-8.445298	11.65889	-0.72	0.4714
# AF GR	-0.69982	0.228465	-3.06	0.0032
Tot AF	0.3254449	0.050372	6.46	<.0001
# Marine AD	-0.076768	0.027008	-2.84	0.0060
# Navy AD	0.439369	0.130199	3.37	0.0013
Sched Pax	0.1381863	0.040998	3.37	0.0013
# Reverse Travel	0.3717535	0.116101	3.20	0.0021
# Agg Mil	0.031726	0.040706	0.78	0.4386
Weekend Flight[0]	-8.995767	2.728113	-3.30	0.0016
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0.0012832	0.000448	2.86	0.0056
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0.0115661	0.005216	2.22	0.0301

Durbin-Watson

Durbin-Watson	Number of Obs.	AutoCorrelation
1.9273088	76	0.0140

Figure 23. 4th Reduced Model

Custom Test

Fifth to fourth model

Parameter		
Intercept	0	0
# AF GR	0	0
Tot AF	0	0
# Marine AD	0	0
# Navy AD	0	0
Sched Pax	0	0
# Reverse Travel	0	0
# Agg Mil	0	0
Weekend Flight[0]	0	0
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0	0
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0	0
(Tot AF-40.0658)*(Sched Pax-316.118)	0	1
=	0	0

Value	0	-0.001991101
Std Error	0	0.0010462501
t Ratio	0	-1.903083633
Prob>|t|	1	0.0615294332
SS	0	1625.1863609

Sum of Squares	1625.1863609
Numerator DF	1
F Ratio	3.6217273151
Prob > F	0.0615294332

WARNING: Non-Testable Contrast

Figure 24: F-test Comparison: 4th Model to Final Model

Custom Test

Full model to final reduced model

Parameter		
Intercept	0	0
#GR	0	1
# AF GR	0	0
Tot AF	0	0
# Marine AD	0	0
# Navy AD	0	0
Sched Pax	0	0
# Single ULNs	0	1
# ULNs > 1	0	1
# ULNs > 5	0	1
# ULNs > 100	0	1
Tot ULNs	0	1
# Dest Diff APOD	0	1
# Reverse Travel	0	0
# Agg Mil	0	0
Weekend Flight[0]	0	0
(Tot AF-40.0658)*(# Reverse Travel-20.8947)	0	1
(Sched Pax-316.118)*(# Agg Mil-75.1053)	0	0
(# Dest Diff APOD-229.355)*(# Agg Mil-75.1053)	0	1
(# Navy AD-15.6842)*(# Reverse Travel-20.8947)	0	0
(Tot AF-40.0658)*(Sched Pax-316.118)	0	1
(# ULNs > 5-9.43421)*(# Agg Mil-75.1053)	0	1
=	0	0

Value	0	-2.392769987
Std Error	0	9.9484744088
t Ratio	0	-0.240516273
Prob>|t|	1	0.8108408429
SS	0	26.767012786

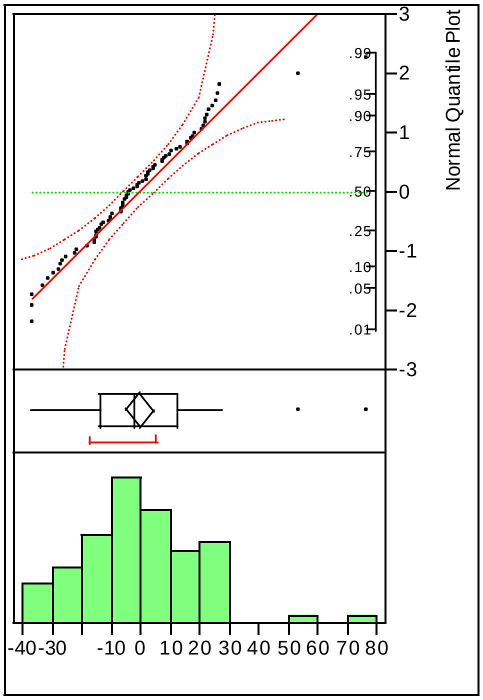
Sum of Squares	26.767012786
Numerator DF	1
F Ratio	0.0578480776
Prob > F	0.8108408429

WARNING: Non-Testable Contrast

Figure 25. F-test Comparison: Full Model to Final Model

Distributions

Residual No-show



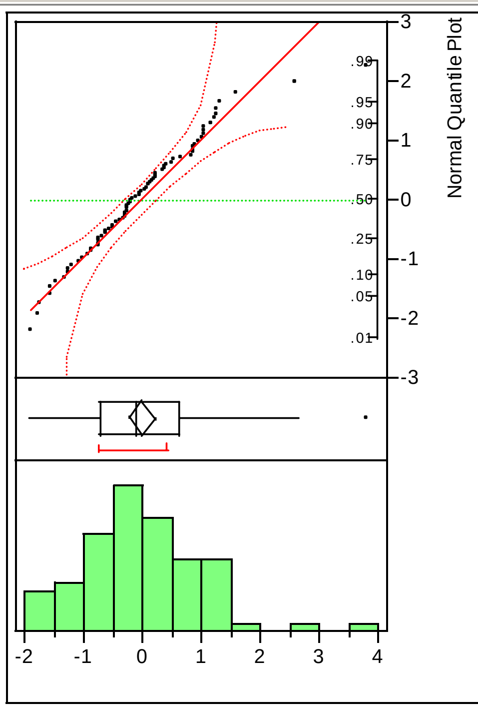
Quantiles

100.0%	maximum	77.42
99.5%		77.42
97.5%		55.93
90.0%		23.43
75.0%	quartile	12.58
50.0%	median	-1.98
25.0%	quartile	-13.43
10.0%		-26.39
2.5%		-35.99
0.5%		-36.15
0.0%	minimum	-36.15

Moments

Mean	-6.06e-14
Std Dev	20.11436
Std Err Mean	2.3072753
upper 95% Mean	4.596328
lower 95% Mean	-4.596328
N	76

Studentized Resid No-show



Quantiles

100.0%	maximum	3.836
99.5%		3.836
97.5%		2.714
90.0%		1.225
75.0%	quartile	0.647
50.0%	median	-0.094
25.0%	quartile	-0.687
10.0%		-1.252
2.5%		-1.751
0.5%		-1.875
0.0%	minimum	-1.875

Moments

Mean	0.0072546
Std Dev	1.0029621
Std Err Mean	0.1150476
upper 95% Mean	0.2364413
lower 95% Mean	-0.221932
N	76

Figure 26. Normality Assumption Verification (Residuals & Studentized)

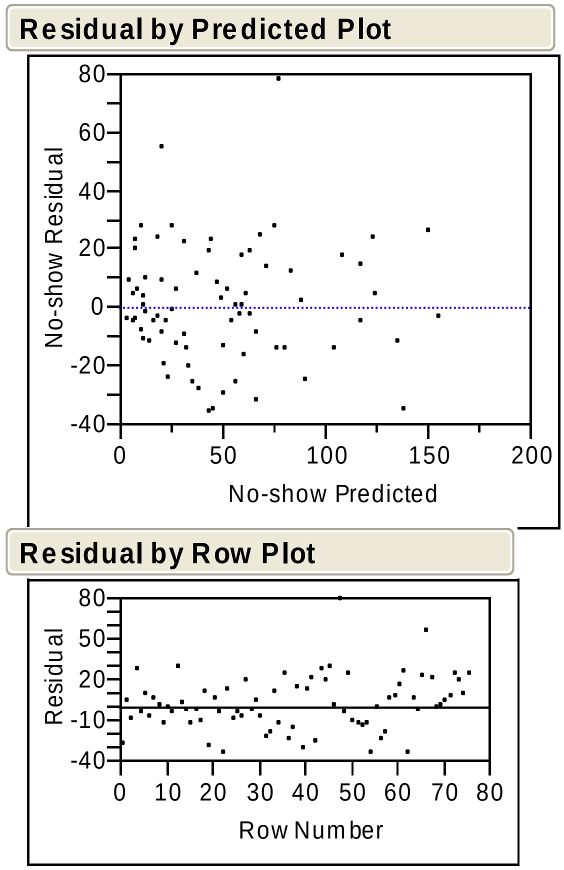


Figure 27. Constant Variance Assumption Verification

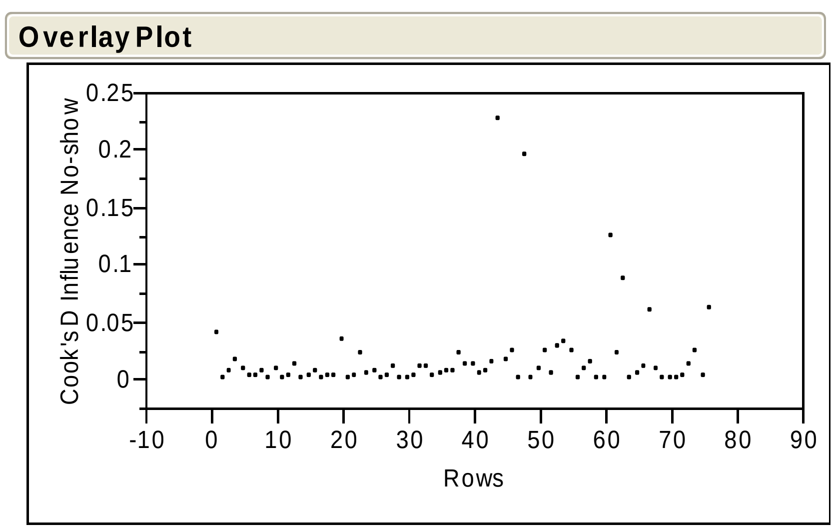


Figure 28. Cook's D Influence

Appendix F: Validation of Model

Table 13. Validation of Test Set Data

Msn	Actual No-shows	Predicted No-show	Nominal Predicted No-shows	Lower 95% PI	Higher 95% PI	Actual Within Interval
J403BL	13	11.9213986	12	-33.637604	57.4804013	In
M402BL	7	12.7254184	13	*	*	*
J405CG	20	109.142349	109	*	*	*
J406CG	3	39.3267939	39	-4.9450271	83.5986149	In
J407CG	47	5.05973612	5	-39.615895	49.7353669	In
J408CG	20	56.1835128	56	11.5727027	100.794323	In
J401CG	2	26.4972329	26	-19.482412	72.4768776	In
A406CG	35	51.1549818	51	4.03617364	98.2737899	In
J410CG	4	33.1216368	33	-14.241487	80.4847606	In
M401CG	44	32.3262002	32	-14.354356	79.0067559	In
M402CG	-2	9.29021065	9	-35.512875	54.0932968	In
A403CG	32	36.5480922	37	-7.7145039	80.8106883	In
A405CG	52	43.5029428	44	-1.9065935	88.9124791	In
J407CG	53	86.5111584	87	41.7371502	131.285167	In
M408CG	39	34.5282863	35	-12.600029	81.6566016	In
M410CG	14	10.5306964	11	-33.544758	54.6061507	In
M404CD	10	3.21701082	3	-41.682419	48.1164406	In
M406CD	42	21.8727353	22	-22.983063	66.7285334	In
M407CD	8	28.1262704	28	-17.098647	73.3511881	In
J405RK	72	57.5779338	58	11.5507095	103.605158	In
J403RK	88	108.969781	109	60.5135685	157.425993	In
J407RK	141	74.5729005	75	22.2559125	126.889888	Out
J408RK	49	42.6078383	43	-2.066422	87.2820986	In
J410RK	87	101.157133	101	50.2569793	152.057286	In
J453RK	100	88.7120191	89	40.3717285	137.05231	In
J405UF	51	76.324938	76	26.4974176	126.152459	In
J408UF	88	58.2005089	58	11.7319003	104.669117	In
J408UF	38	34.6342206	35	*	*	*
J409UF	126	106.161305	106	57.2117052	155.110904	In
J413UF	69	107.35836	107	61.6117185	153.105002	In

Bibliography

Air Mobility Command. "Charters - Special Assignment Airlift Missions (SAAMs), Joint Chiefs of Staff Exercises, and Contingencies for the Transportation Working Capital Fund (TWCF), and Non-TWCF Aircraft." Air Mobility Command document. Scott AFB, IL: HQ AMC/FMP. 2003.

Bean, Andre B. & Talaga, James. "Predicting Appointment Breaking," *Journal of Health Care Marketing*, 15: 29-35 (Spring 1995).

Beckmann, Martin J. (1958). "Decision and Team Problems in Airline Reservations," *Econometrica, 26:* 134-145 (January 1958).

Belobaba, P. P. *Air Travel Demand and Airline Seat Inventory Management.* Report R87-7, Cambridge, MA: Flight Transportation Laboratory, MIT, 1987.

Browne, Ken S. *Using RSM, DOE, and Linear Regression to Predict Cargo Delivery of a Time Phase Force Deployment Document.* MS thesis, AFIT/GOA/ENS/00-01. School of Engineering, Air Force Institute of Technology (AU), Wright-Patterson AFB OH, March 2000.

Chairman of the Joint Chiefs of Staff. *CJCS Exercise Program Funding*. CJCSI 3511.01. Washington: Joint Staff, 30 July 1999.

Chairman of the Joint Chiefs of Staff. *Crisis Action Time-Phased Force and Deployment Data Development and Deployment Execution, Volume III.* CJCSM 3122.02A. Washington: Joint Staff, 17 July 2000.

Chairman of the Joint Chiefs of Staff. *Joint Tactics, Techniques and Procedures for Airlift Support to Joint Operations.* Joint Pub 4-01.1. Washington: Joint Staff, 20 July 1996.

Curry, R. E. "Parallel Nesting and Overallocation," Abstract, ORSA/TIMS Joint National Meeting Bulletin, San Francisco, California. November 1992.

Curtin, Neal P. *MILITARY READINESS: Civil Reserve Air Fleet Can Respond as Planned, but Incentives May Need Revamping*. Report to the Chairman, Subcommittee on Military Readiness, Committee on Armed Services, House of Representatives GAO 03-278. Washington: GAO, December 2002

Davis, Paul. "Airline Ties Profitability Yield to Management," *SIAM News*, 27(5), (May/June 1994). http://www.siam.org/siamnews/mtc/mtc694.htm.

Department of the Air Force. *Civil Reserve Airlift Fleet*. Excerpt from unpublished article. N. pag. July 2004. http://www.af.mil/factsheets/factsheet.asp?fsID=173.

Farnham, Alan. "Denied Boarding (Overbooking by Airlines)," *Forbes*, 167: 112. (June 2001).

Freisleben, Bernd and Gleichmann, Gernot. "Controlling Airline Seat Allocations with Neural Networks," *System Sciences*, 4: 635-642. (January 1993).

Garuda, Sanjay R, Javalgi, Rajshekhar G., and Talluri, Vijay S. "Tackling No-Show Behavior: A Market-Driven Approach," *Health Marketing Quarterly*, 15: 25-45, (Winter 1998).

Graham, David. *Sustaining the Civil Reserve Air Fleet (CRAF) Program*. The Institute for Defense Analyses, Report for Office of the Deputy Under Secretary of Defense for Logistics and Materiel Readiness, May 2003.

Gujarati, Damodar N. *Basic Econometrics.* New York: McGraw-Hill, 1995.

Horan, Donald J. "More Effective Use of Contract Airlift Could Reduce DoD's Transportation Costs (GAO/PLRD-83-55)," Memorandum to the Secretary of Defense, Washington: GAO, 22 April 1983.

Headquarters Air Mobility Command. "Health of the Force: C-5 Aircraft." Briefing, June 2004a https://amclg.scott.af.mil/hof/docs/c5.pdf.

Headquarters Air Mobility Command. "Health of the Force: C-17 Aircraft." Briefing, June 2004b https://amclg.scott.af.mil/hof/docs/c17.pdf

Ignaccolo, Matteo & Inturri, Giuseppe. "A Fuzzy Approach to Overbooking in Air Transportation," *Journal of Air Transportation World Wide,* 5: 19-38 (Spring 2000).

James, George. *Airline Economics*. Lexington, MA: Lexington Books, 1982.

Lawrence, Richard D., Hong, Se June, and Cherrier, Jacques. "Passenger-Based Predictive Modeling of Airline No-Show Rates," *Proceedings of the Ninth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining,* 397—406. Washington: ACM, August 2003.

Littlewood, K. "Forecasting and Control of Passenger Bookings," *Proceedings 12th AGIFORS Symposium*, 95-117. New York: American Airlines, 1972

McClave, James T., Benson, P. George, and Sincich, Terry. *Statistics for Business and Economics.* New Jersey: Prentice-Hall Inc., 1998.

Miller, Mark. "It's Time to Tackle the No-Show Problem." *Restaurant Hospitality*: 76: 50 (May 1992).

Neter, John and others. *Applied Linear Statistical Models*. Chicago: Irwin, 1996.

Peterkofsky, David. "Overbooked, Overwrought – Overblown?" *Travel Age West,* 8 July 8, p. 1, 49. 2002

Pike, Christopher A. *Duty Passenger Travel: Education and Analysis*. Graduate Research Paper, AFIT/GMO/LAL/98J-13. School of Logistics and Acquisition Management, Air Force Institute of Technology (AU), Wright-Patterson AFB OH June 1998

Rothstein, M., and A. W. Stone. "Passenger Booking Levels," *Proceedings 7th AGIFORS Symposium.* New York: American Airlines, 1967

Ruppenthal, Karl M. and Toh, Rex. "Airline Deregulation and the No Show/Overbooking Problem," *Logistics and Transportation Review*, 19: 111-122, (June 1983).

Schmidt, Rachel. *Moving U.S. Forces: Options for Strategic Mobility*. Congress of the United States. Washington: Congressional Budget Office, February 1997

Smith, B. C., J. F. Leimkuhler, and R. M. Darrow. "Yield Management at American Airlines," *Interfaces*, 22: 8-31, (January 1992).

Taylor, C. J. "The Determination of Passenger Booking Levels," *Proceedings 2nd AGIFORS Symposium.* 93-116. New York: American Airlines, 1962.

Thompson, H. R. "Statistical Problems in Airline Reservation Control," *Operational Research Quarterly*, 12: 167-185. (1961)

USCINCTRANS. "In-transit Visibility Progress." Electronic Message. 212118Z, 21 October 2000.

Weatherford, L. R., and S. E. Bodily. "A taxonomy and Research Overview of Perishable-Asset Revenue Management: Yield Management, Overbooking, and Pricing," *Operational Research Quarterly*, 40: 831-844 (September 1992)

Zaki, Hossam. "Forecasting for Airline Revenue Management," *The Journal of Business Forecasting*, 19: 2-6 (Spring 2000).

Zhao, Wen & Zheng, Yu-Sheng. "A Dynamic Model for Airline Seat Allocation with Passenger Diversion and no-Shows," *Transportation Science*, 35: 80-98 (February 2001).

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 074-0188*

The public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of the collection of information, including suggestions for reducing this burden to Department of Defense, Washington Headquarters Services, Directorate for Information Operations and Reports (0704-0188), 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to an penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.
PLEASE DO NOT RETURN YOUR FORM TO THE ABOVE ADDRESS.

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From – To)*
03-09-2004	Graduate Research Project	Sept 2003 – Sept 2004

4. TITLE AND SUBTITLE	
MODELING NO-SHOW PASSENGERS ON PACOM EXERCISE AIRLIFT	**5a. CONTRACT NUMBER**
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	**5d. PROJECT NUMBER**
Chadwick, Glenn S., Major, USAF	**5e. TASK NUMBER**
	5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S)	**8. PERFORMING ORGANIZATION REPORT NUMBER**
Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Way, Building 640 WPAFB OH 45433-8865	AFIT/MLM/ENS/04-02
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	**10. SPONSOR/MONITOR'S ACRONYM(S)**
N/A	**11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

12. DISTRIBUTION/AVAILABILITY STATEMENT

APPROVED FOR PUBLIC RELEASE; DISTRIBUTION UNLIMITED.

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The issue of no-shows plagues many different industries that rely on reservation or appointment-type processes. Everything from the restaurant to healthcare to commercial airline industry has had to come up with solutions to this problem in order to remain both profitable and customer-service oriented. Many of these industries have used statistical models to predict no-shows such that seats or appointments that would otherwise go unused are filled with customers that were overbooked for those vacancies. This is a balancing act between trying to predict the number of no-shows and planning the number to overbook, without having more customers show up than able to accommodate, a dangling proposition. The military has been dealing with this same problem on its commercially chartered flights that move troops overseas for exercises, contingencies, and other requirements.

This research is aimed at using a statistical model to predict the number of no-shows on chartered passenger airlift for Pacific Command joint exercises to try to maximize the utilization of seats left unused by no-shows through overbooking techniques. If the number of no-shows can be predicted accurately, airlift planners will be able to overbook missions to fill those seats and minimize wasted resources. This will be done using a purely quantitative approach with correlation analysis and building a multiple regression model. The model will be built using both personnel and mission characteristic factors from historical airlift data from major joint exercises in the Pacific Command's area of responsibility..

15. SUBJECT TERMS

No-show passengers, regression, correlation, PACOM, exercise, charter airlift

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
					Kirk A. Patterson., Maj, USAF
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**			**19b. TELEPHONE NUMBER** *(Include area code)*
U	U	U	UU	139	(937) 255-6565, ext (Kirk.Patterson@afit.edu)

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std. Z39-18